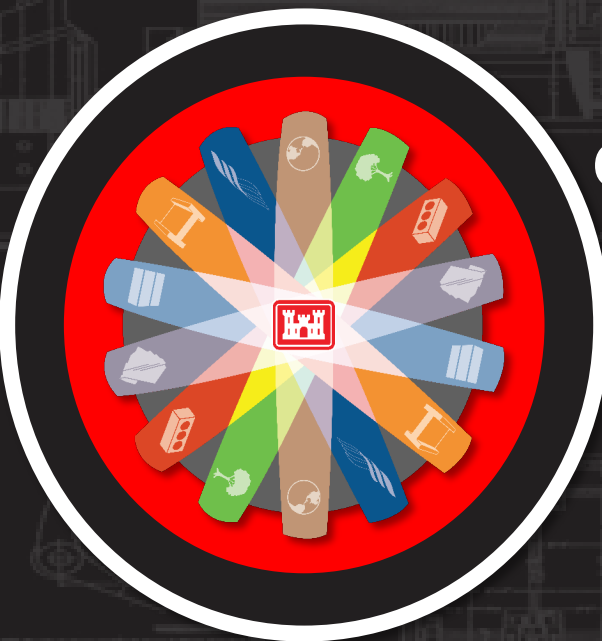




**CONNECTING
THE DOTS TO
INNOVATION**

SIMULATING TIME-DEPENDENT METEOROLOGICAL AND OCEANOGRAPHIC (METOC) CONDITIONS FOR COASTAL IMPACTS

Dylan Anderson.... and Nicholas Cohn, Yan Ding, and many more



U.S. ARMY



**US Army Corps
of Engineers®**



ERDC
ENGINEER RESEARCH & DEVELOPMENT CENTER

Funding from CODS (FY23-25)
And primarily the Navy (FY24-26)



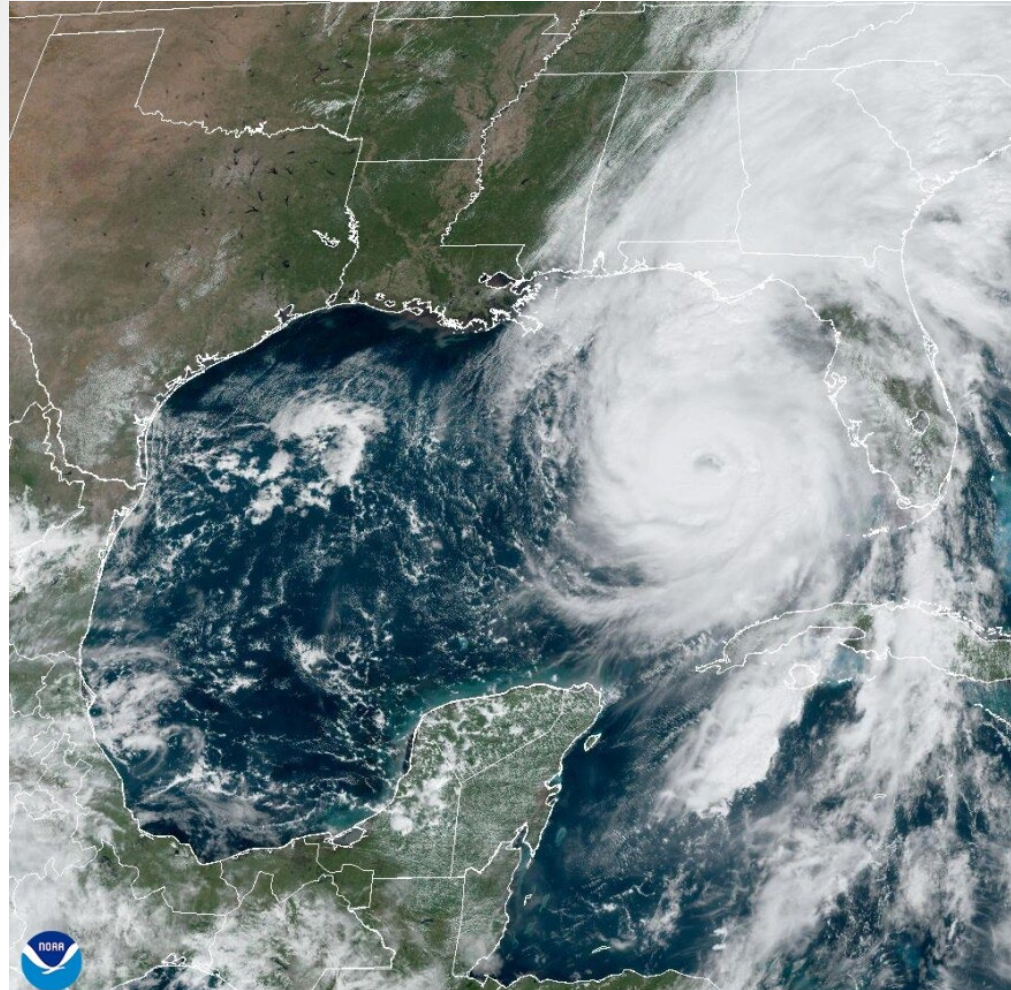


UNCLASSIFIED

THE EXTREME AND THE CHRONIC – MULTIPLE TIMESCALES



Extreme Coastal Storm Hazards



26 Sep 2024 16:31Z - NOAA/NESDIS/STAR - GOES-East - GEOCOLOR Composite - GM

Hurricane Helene

Persistent and Increasing Problems

Nuisance/Sunny Day Flooding: Multiple Timescales



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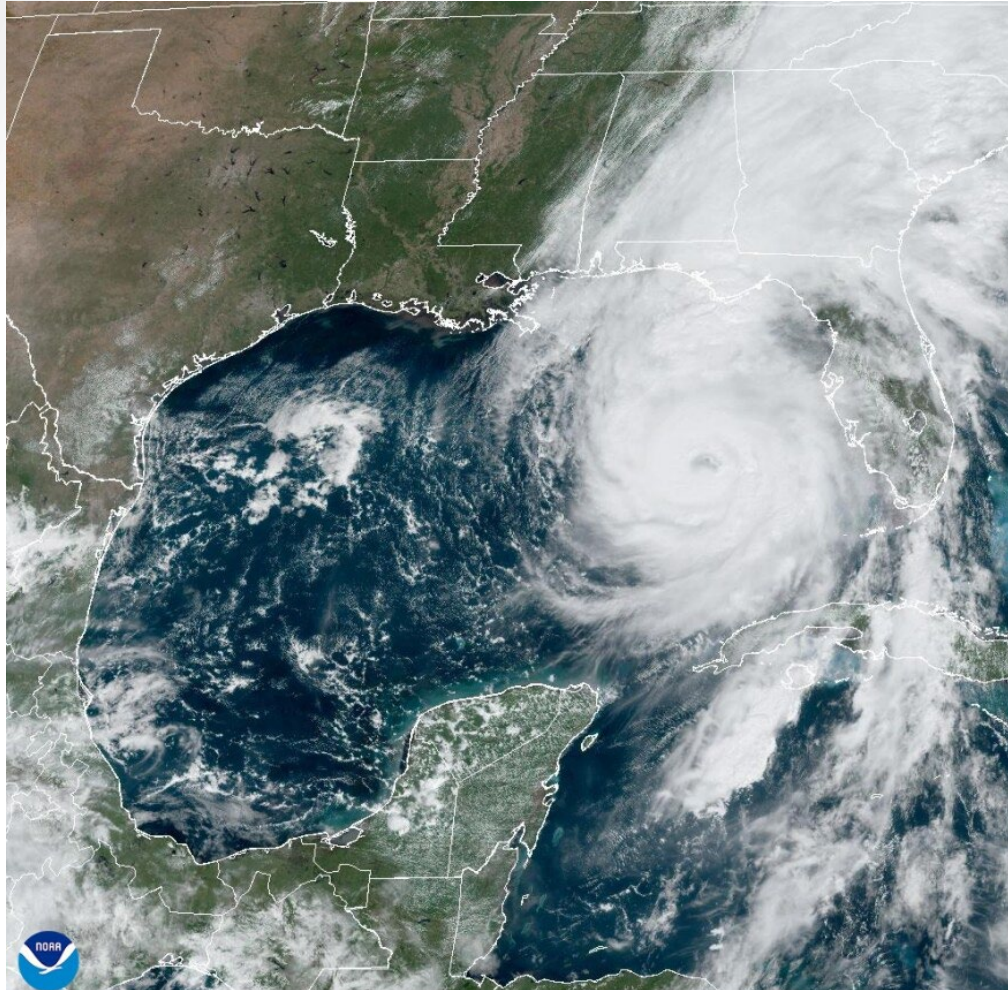


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THE EXTREME AND THE CHRONIC – SUBSIDENCE



Extreme Coastal Storm Hazards



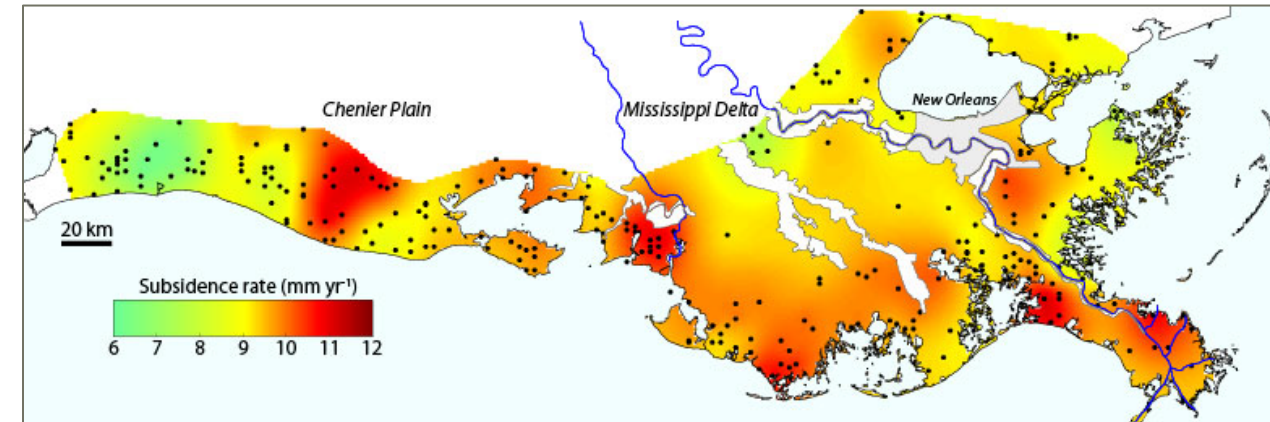
26 Sep 2024 16:31Z - NOAA/NESDIS/STAR - GOES-East - GEOCOLOR Composite - GM

Hurricane Helene

Persistent and Increasing Problems

Nuisance/Sunny Day Flooding

Subsidence (Natural + Engineered)



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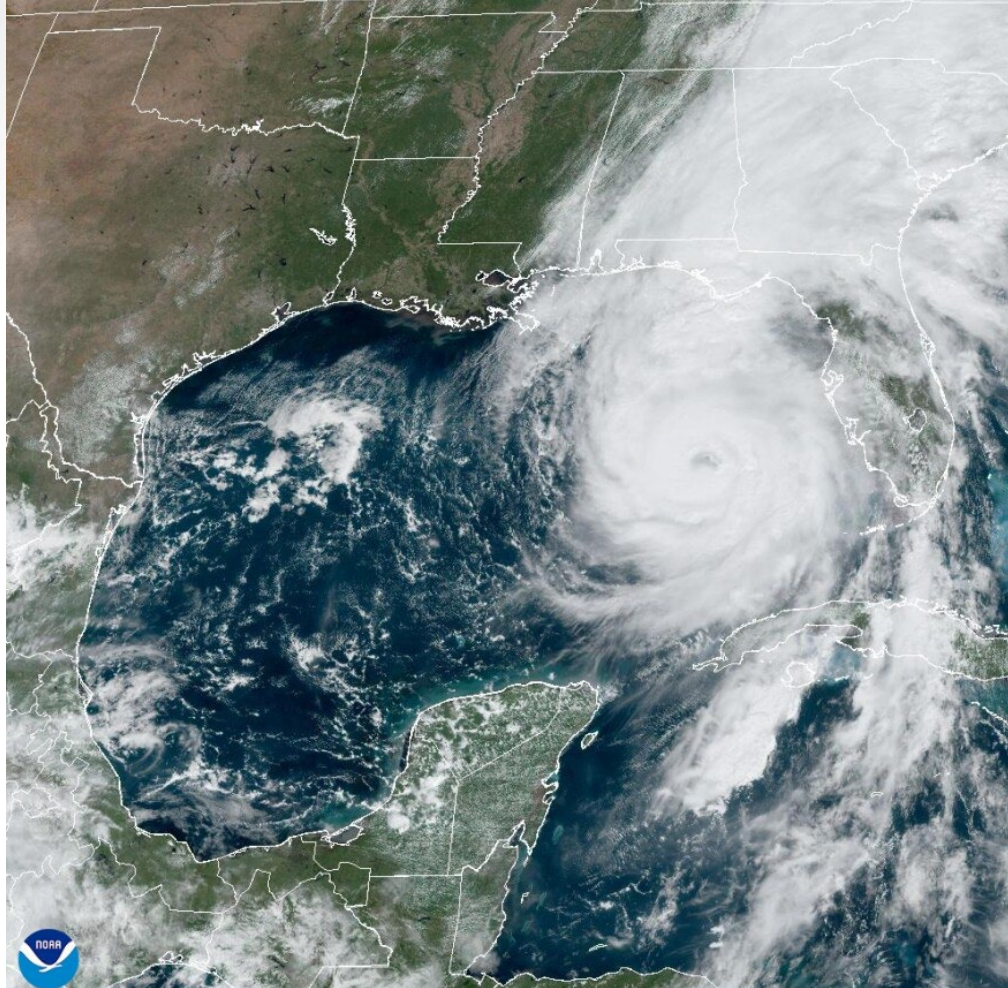


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THE EXTREME AND THE CHRONIC – SHORELINE EROSION



Extreme Coastal Storm Hazards



26 Sep 2024 16:31Z - NOAA/NESDIS/STAR - GOES-East - GEOCOLOR Composite - GM

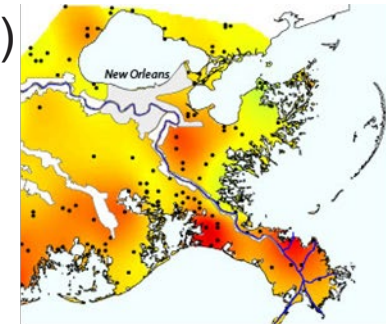
Hurricane Helene

Persistent and Increasing Problems

Nuisance/Sunny Day Flooding

Subsidence (Natural + Engineered)

Shoreline Erosion (Protection measures)

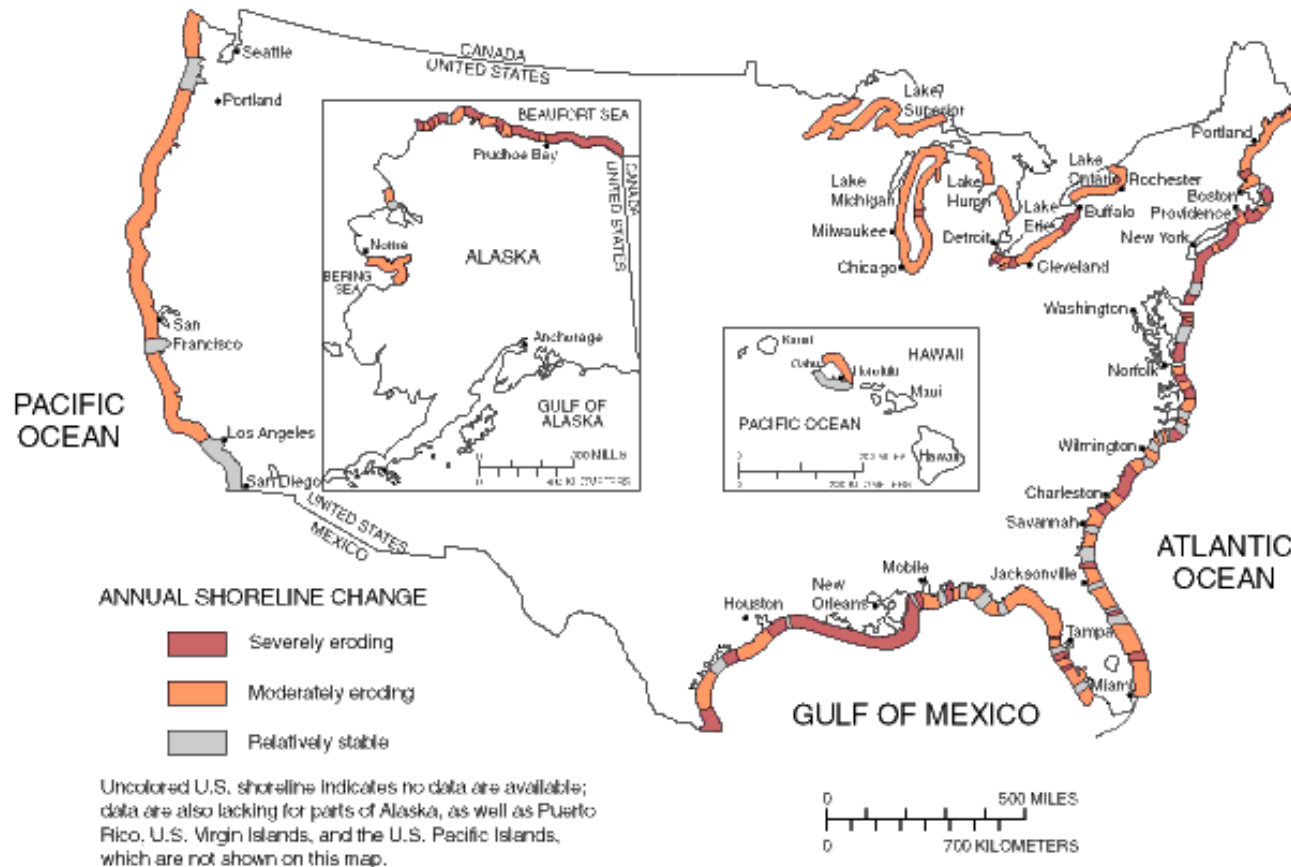


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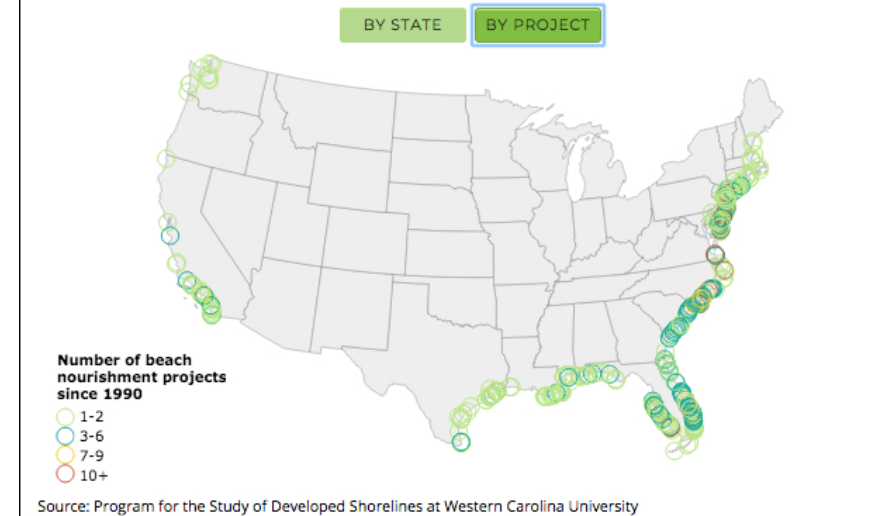
THE EXTREME AND THE CHRONIC

An immense length of coastline needing protection...



Beach Nourishment Boom

States, localities and the federal government have spent more than \$6.5 billion since 1990 pumping sand onto beaches to fight erosion and rising seas. Click on the map to view spending by state and by project.



Need the ability to forecast:

- to simulate water levels, morphology change
- to see lifecycles of resiliency measures,
- to prepare budgets for interventions,
- to identify where the only option is retreat



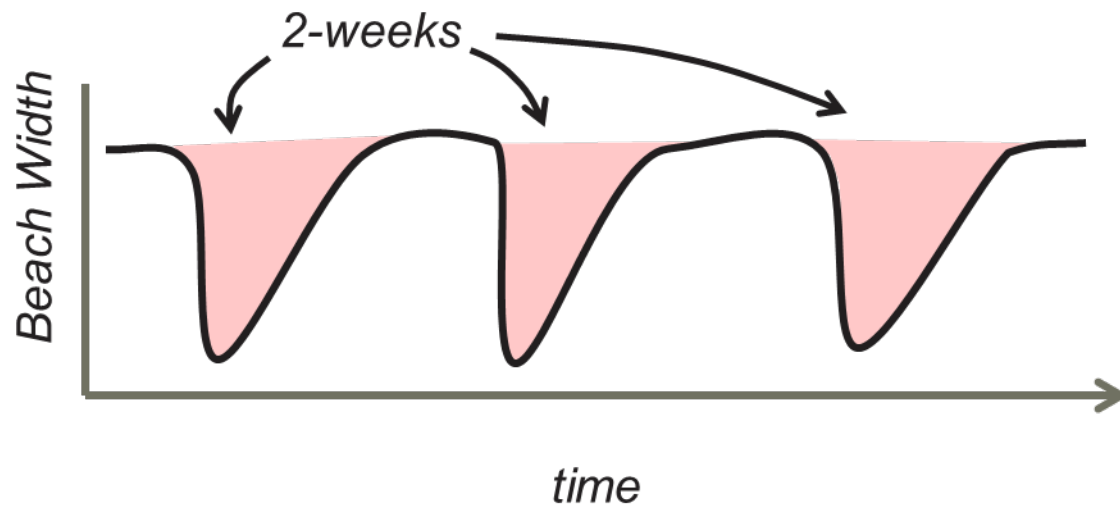
MULTI-DECADAL MORPHOLOGY PREDICTIONS



Planned beta replacement for Beach-fx

Life-cycle modeling of the beach includes unique storm effects but generic rule for recovery (default of 90% in 2-weeks)

- Background erosion rate between storms: waves are not explicitly accounted for.
- State of the beach is not accounted for during recovery.



Coastal Hazards Analysis and Risk Toolkit

$\text{Risk} = f(\text{Hazards, Physical System Response, Exposure, Vulnerability})$

Hazards

- Erosion (storm, background)
- Wave Impacts
- Storm Surge
- Sea Level Change
- Fluvial/Pluvial Flooding

Physical System Measures

- Flood/Seawalls
- Dune/Beach Nourishment
- Groins
- Offshore Breakwaters
- Natural and Nature-Based Features
- Levees

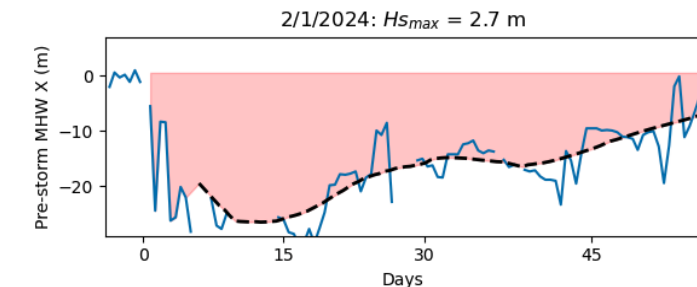
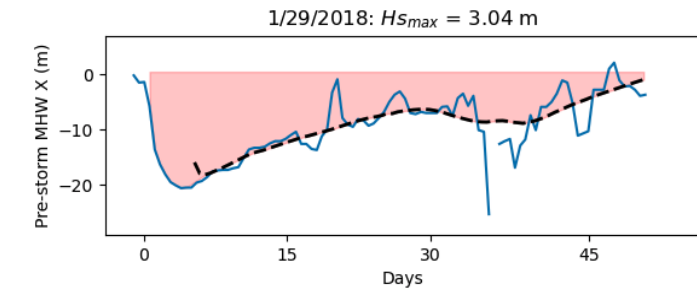
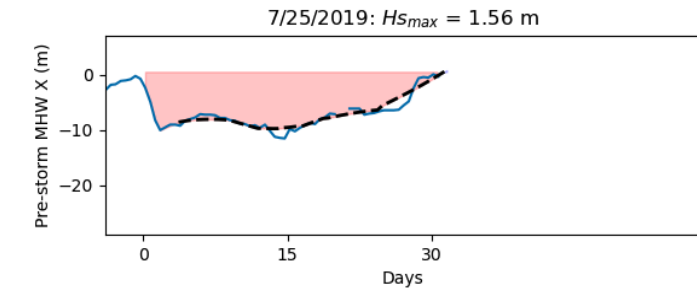
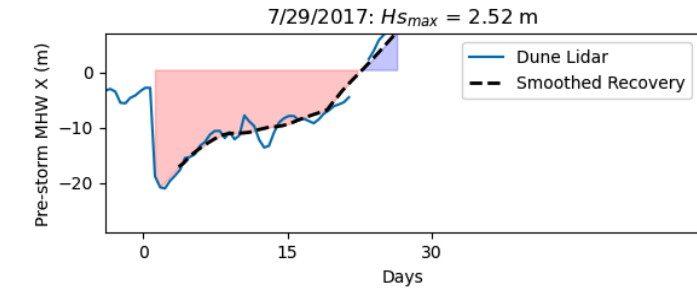
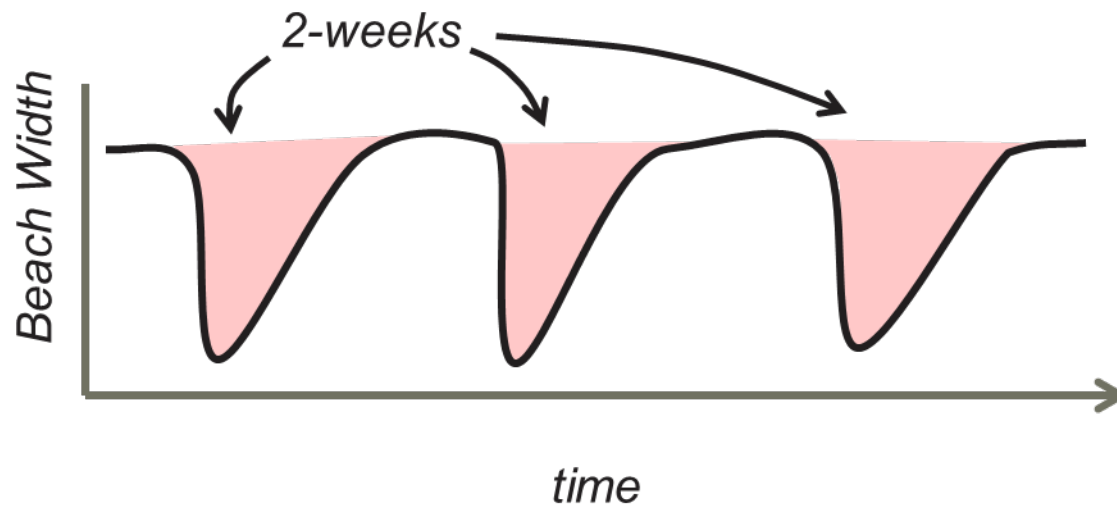
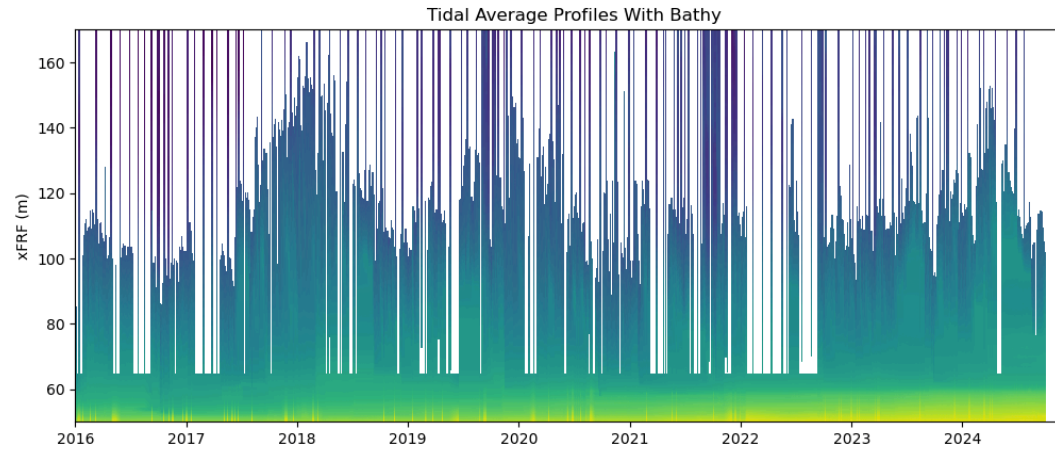




WHAT DOES REAL DATA SHOW?

Extracting MHW contour from Dune Lidar

- Wide range of recovery timelines over the last 8 years

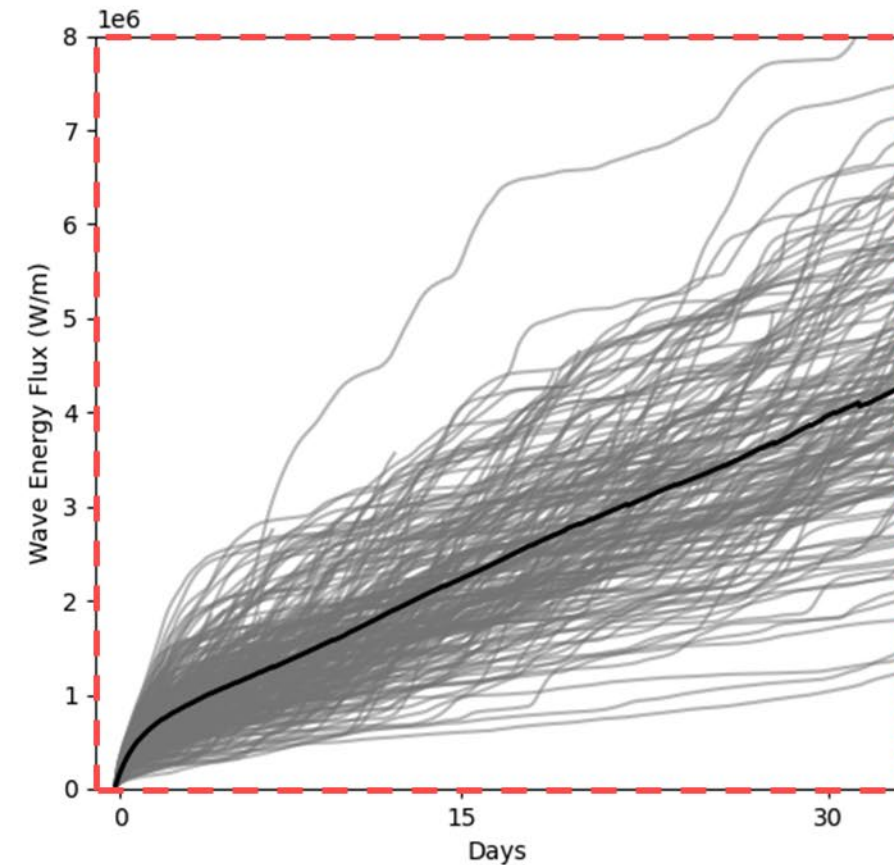
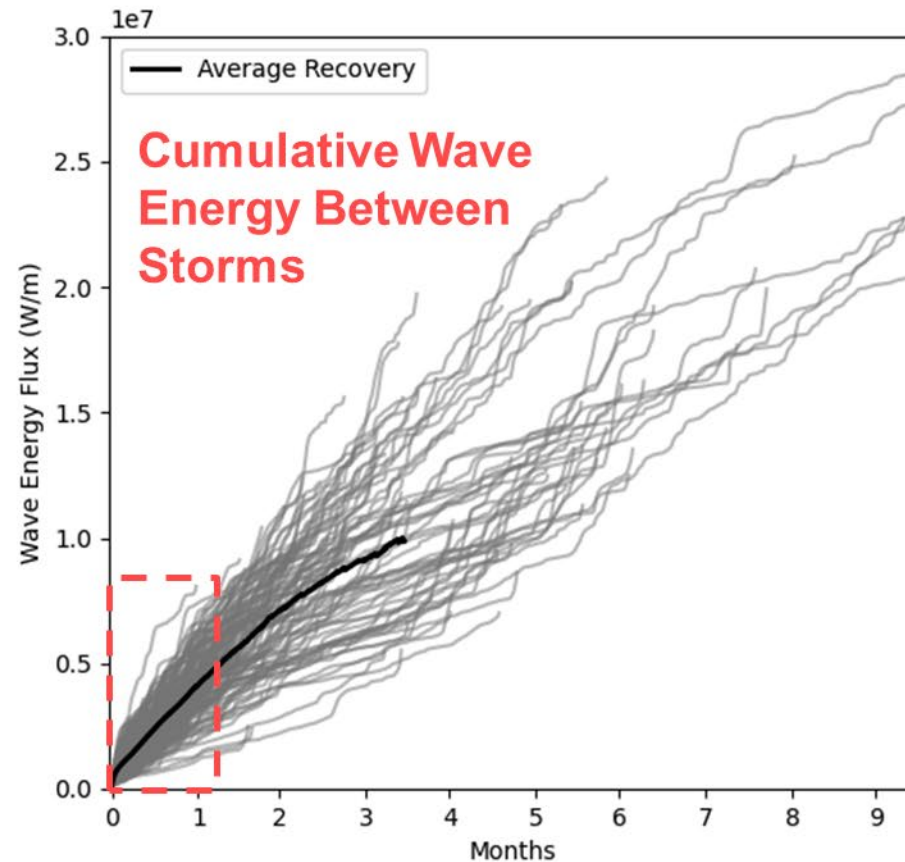




BUT VARIABILITY SHOULD BE EXPECTED

Many factors contributing to variability in beach recovery

- Initial beach state
- seasonality in storm occurrence
- dependence on storm severity
- inter-storm weather, wind, waves





SAME FOR THE COMPONENTS OF TWLS

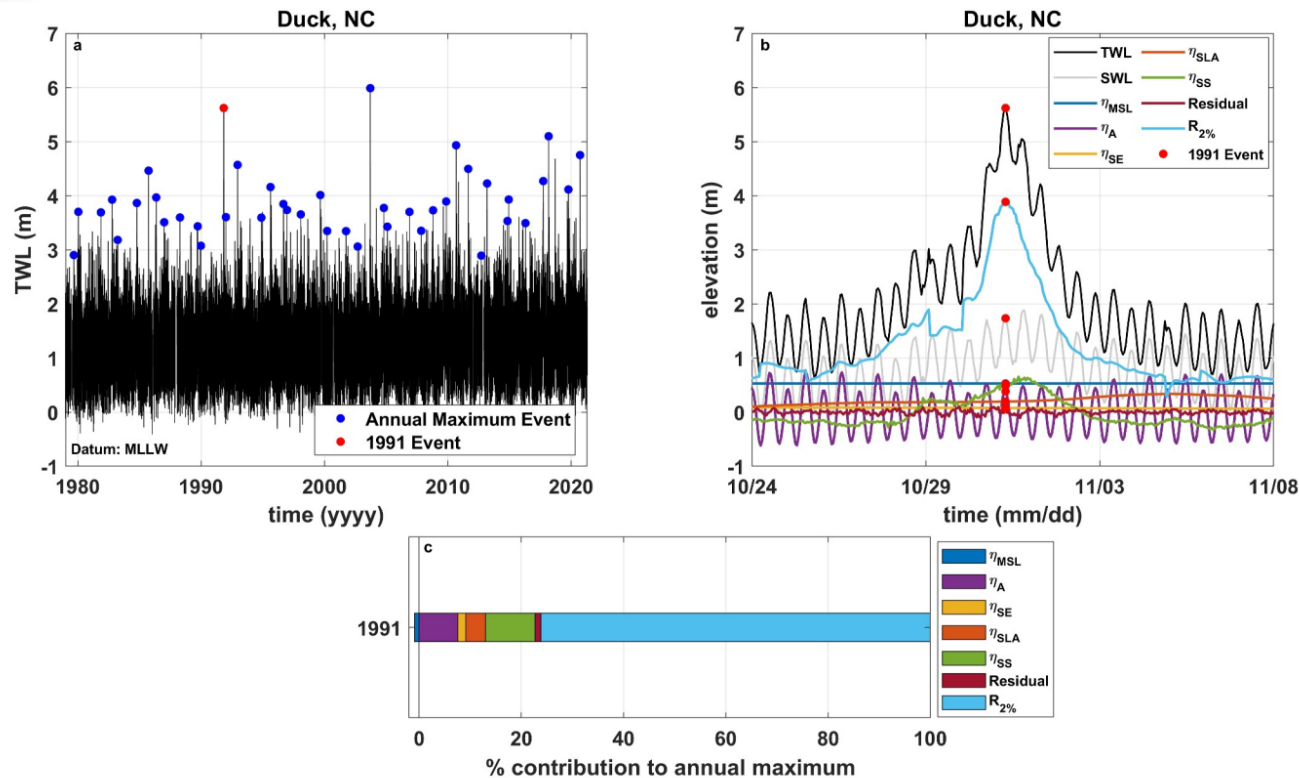


Figure 2. Example steps for determining the relative contribution of individual water level components to TWLs at Duck, NC. Annual maximum TWL events are identified for each year between 1980 and 2020 (a). A red dot highlights the 1991 event. The magnitude of the annual maximum TWL and its drivers, including the still water level (SWL, light gray) and wave runup ($R_{2\%}$, light blue), during the 1991 event is identified, also represented by red dots (b). Then, each component's percent

Quadrado and Serafin (2024)

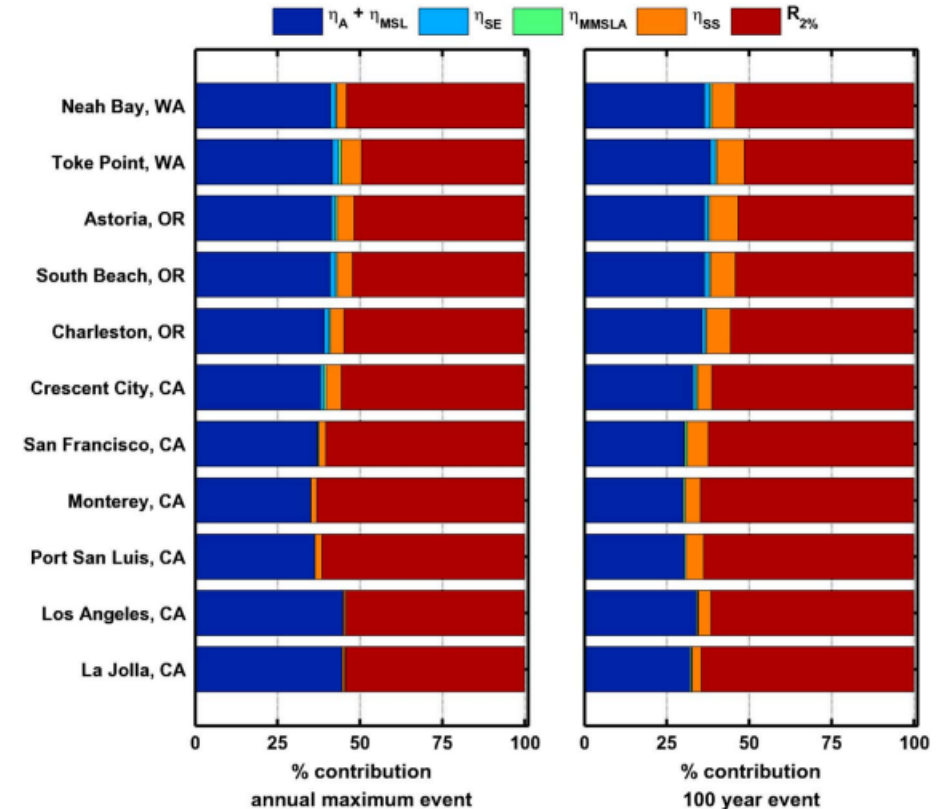


Figure 3. Relative contribution of the individual components to the annual maximum and 100 year TWL event. Bars are plotted from north (Neah Bay, WA) to south (La Jolla, CA). Red represents the wave-driven ($R_{2\%}$) component, while all other colors represent the SWL.

Serafin et al. (2017)



RESPONSE-BASED CHRONOLOGIES

We need to see alternate versions of the future, and continuous time-series of:

Waves and Water level components (tides, NTRs: storm surge, sea level anomalies at bi-weekly, seasonal, annual scales)

Add **winds** for dune evolutions

And **sea ice + temps** for permafrost erosion

And **precip + river flow** for overland flooding

And all of it for wave-driven flooding and storm impacts.

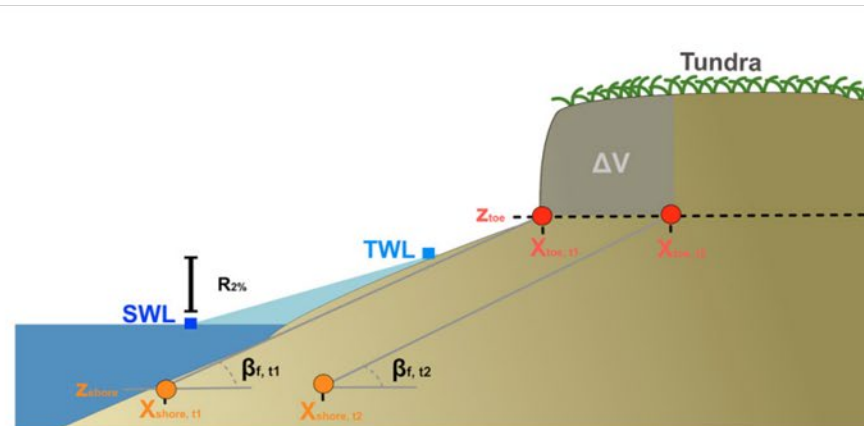
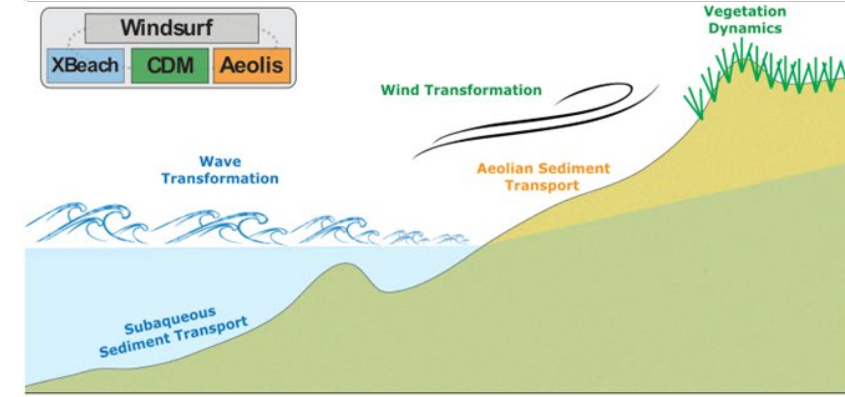
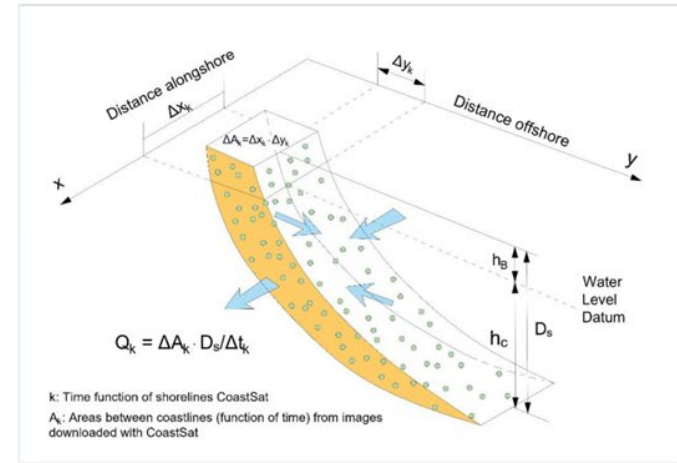
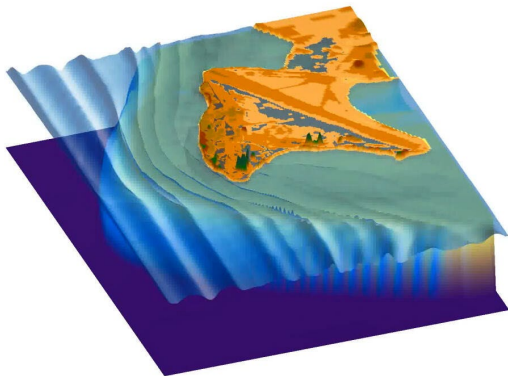
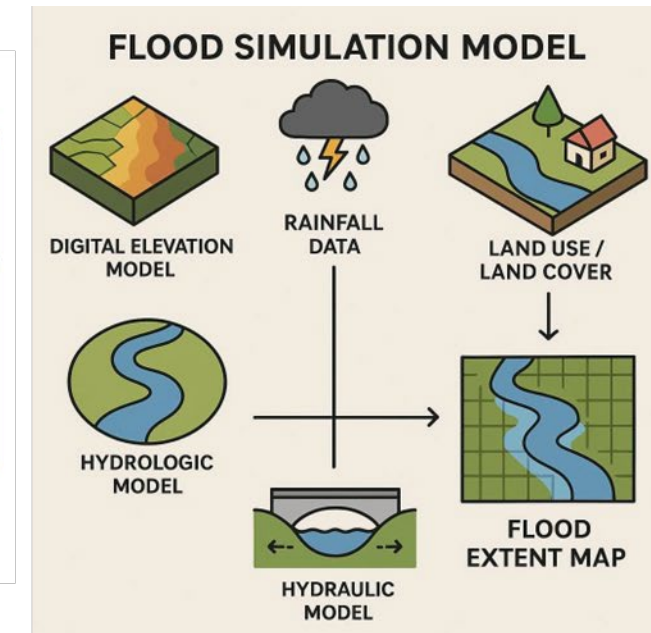
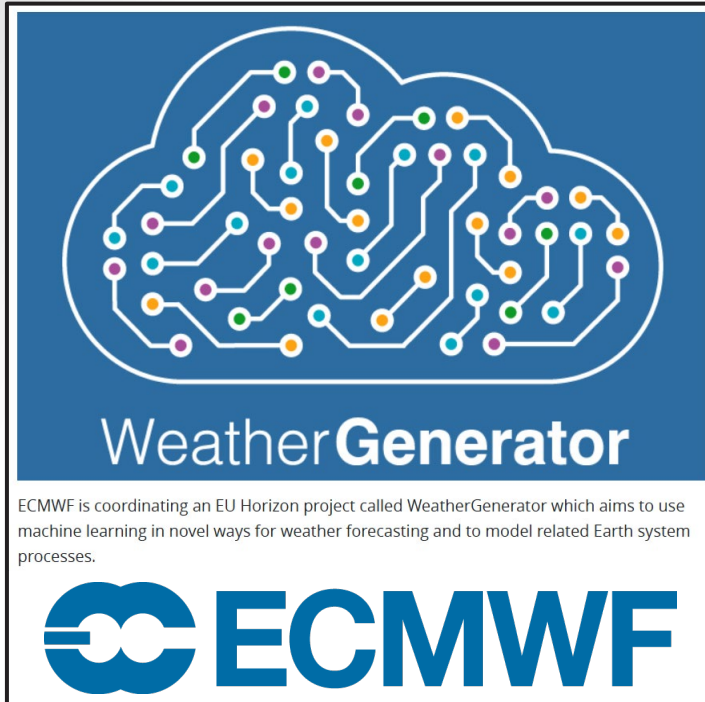


Figure 10. Cross-shore schematic of model definitions.



RETAIN TIME DOMAIN VIA WEATHER EMULATOR

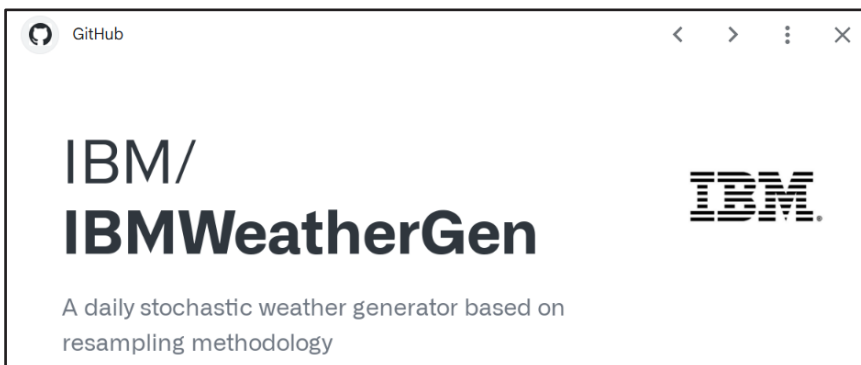
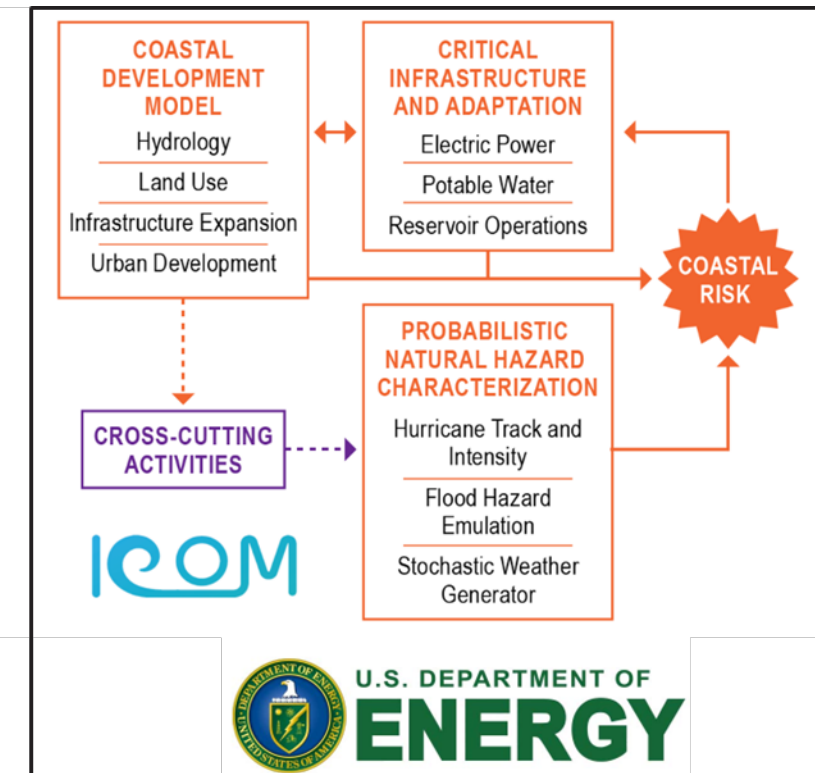


ARTIFICIAL INTELLIGENCE

Google DeepMind's new AI model is the best yet at weather forecasting

The research represents a shift in how we may predict the weather.

Concept: We have “seen” enough variability to predict time series of weather that are statistically-consistent and equally as likely as our observation record.



Progress in Physical Geography 23,3 (1999) pp. 329–357

The weather generation game: a review of stochastic weather models

D.S. Wilks¹ and R.L. Wilby²

¹Atmospheric Science Group, Cornell University, Ithaca, New York, NY 14853, USA
²National Center for Atmospheric Research, Boulder, CO 80307, USA, and Division of Geography, University of Derby, Kedleston Road, Derby DE22 1GB, UK

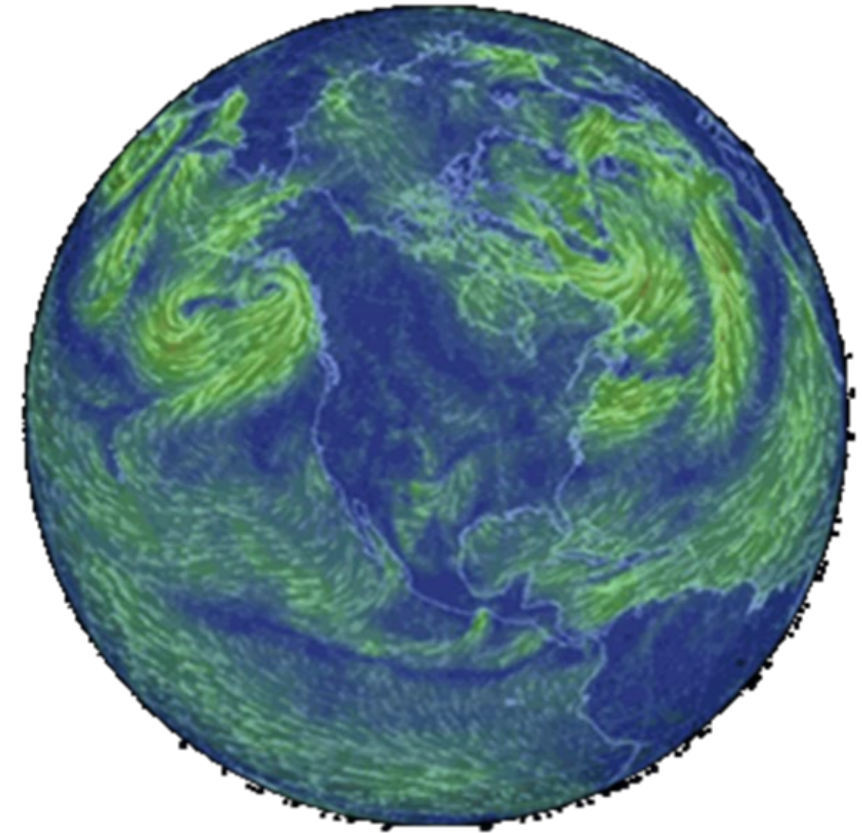
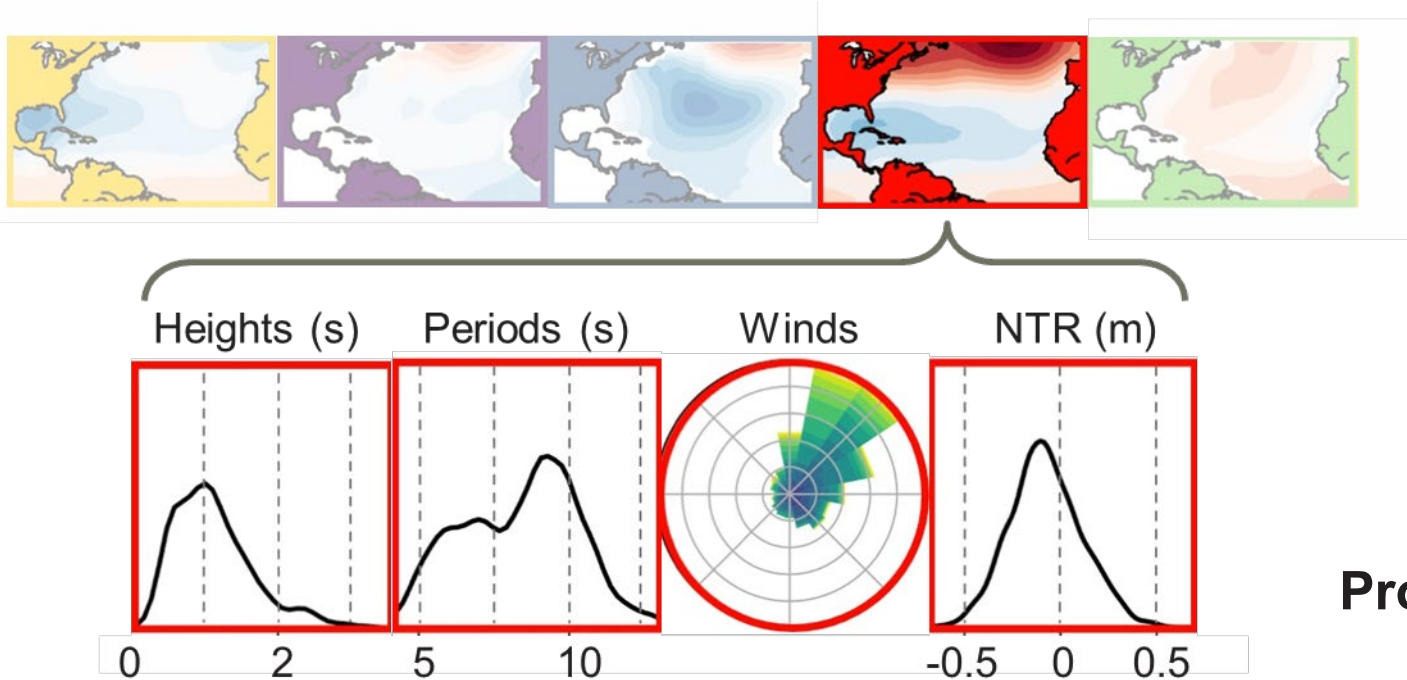


STOCHASTIC WEATHER GENERATOR – ASSUMPTION



Assumption: weather drives local forcing

Weather drives the winds – creating ocean waves, storm surges, and aeolian sediment transport.



Proposal: A data-driven sequencing model

Auto-logistic Regression for synthetic time series of storms and subsequent inter-storm weather chronologies.

A number of options for statistically-downscaling random potential synthetic wave chronologies within each weather pattern (e.g. Cagigal et al. 2021)

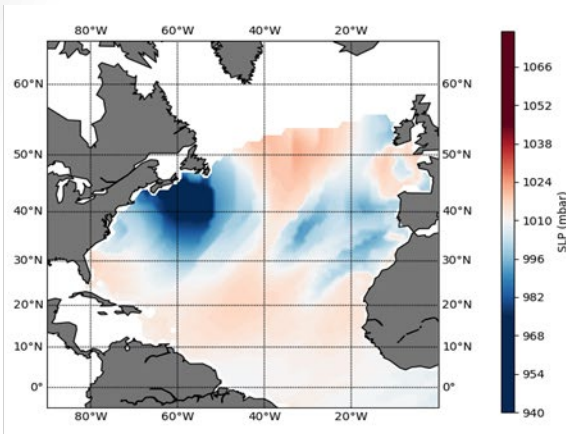


STOCHASTIC WEATHER GENERATOR – WEATHER TYPING



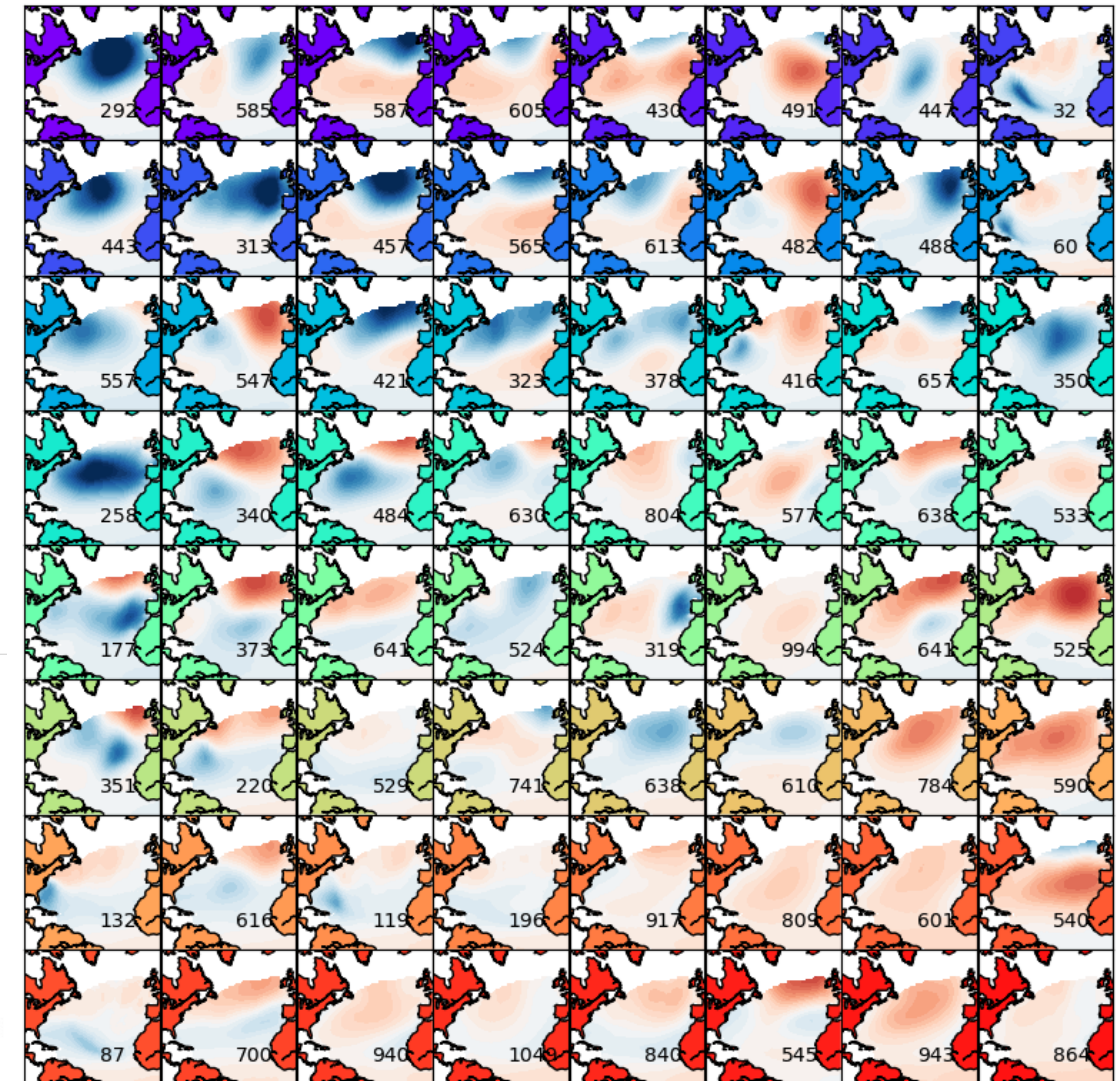
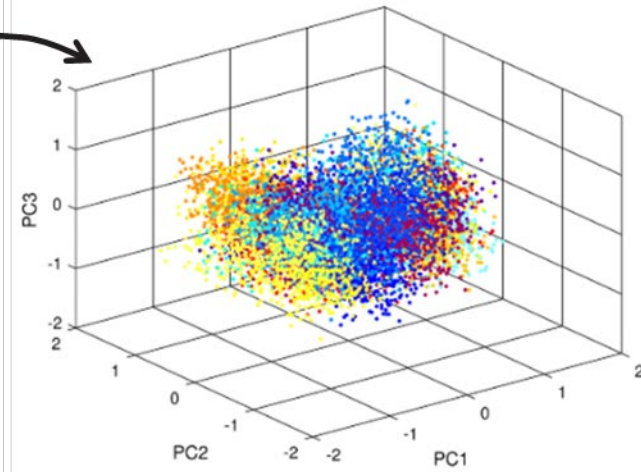
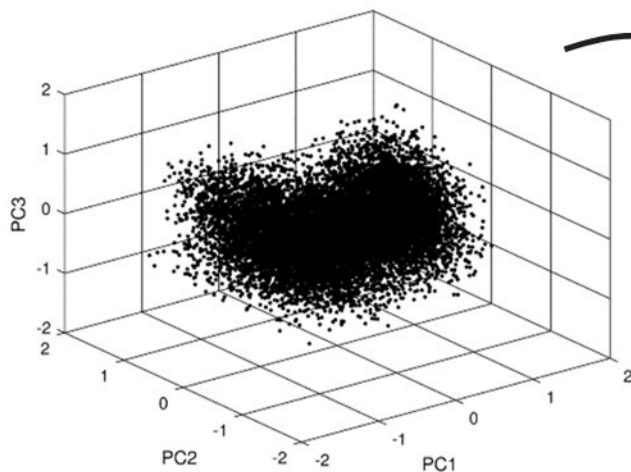
Efficient time-continuous met-ocean conditions

1. Identify common weather patterns



“Weather Typing”

- Principal Component Analysis for dimension reduction
- K-means clustering in reduced dimensions

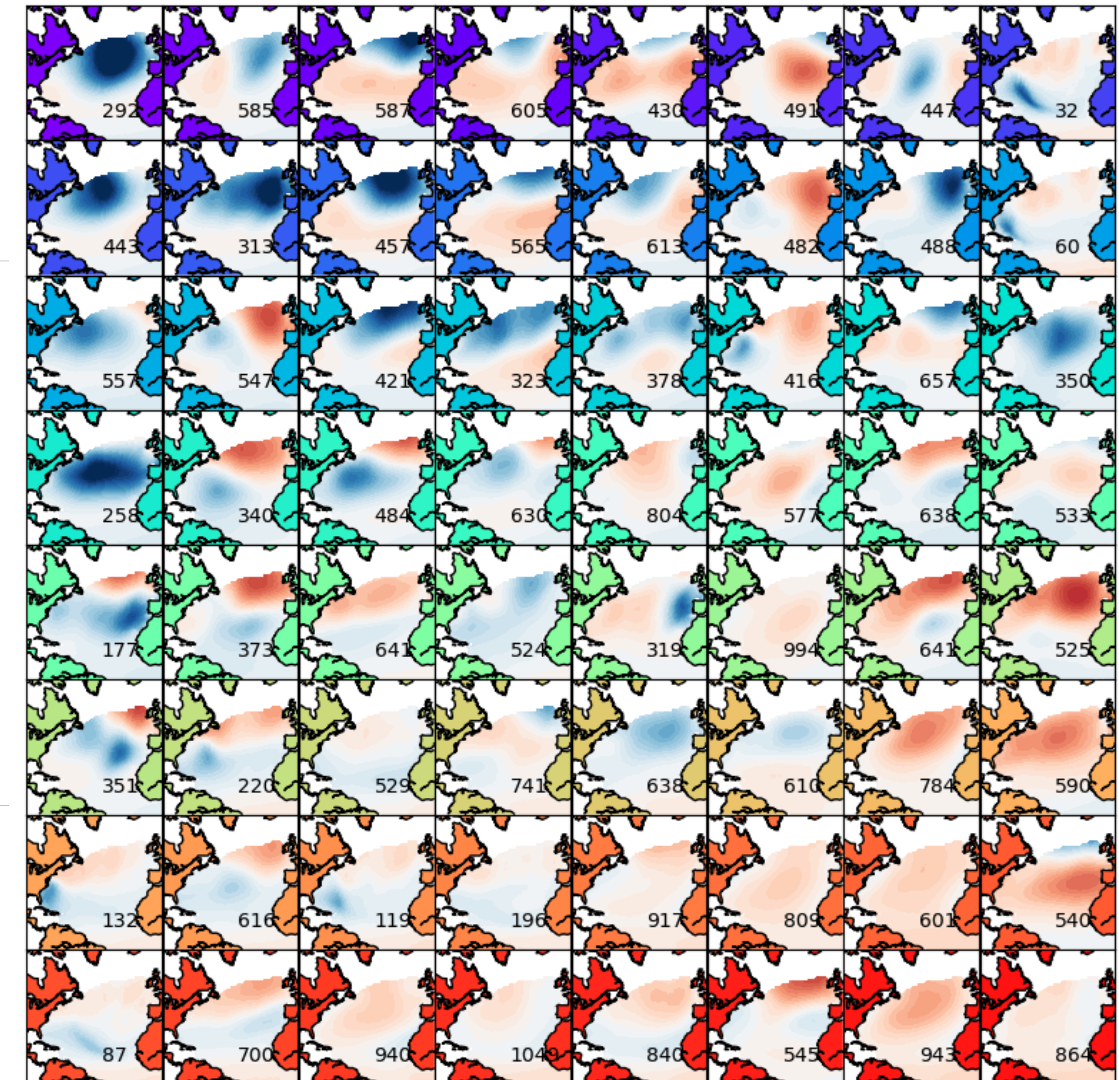
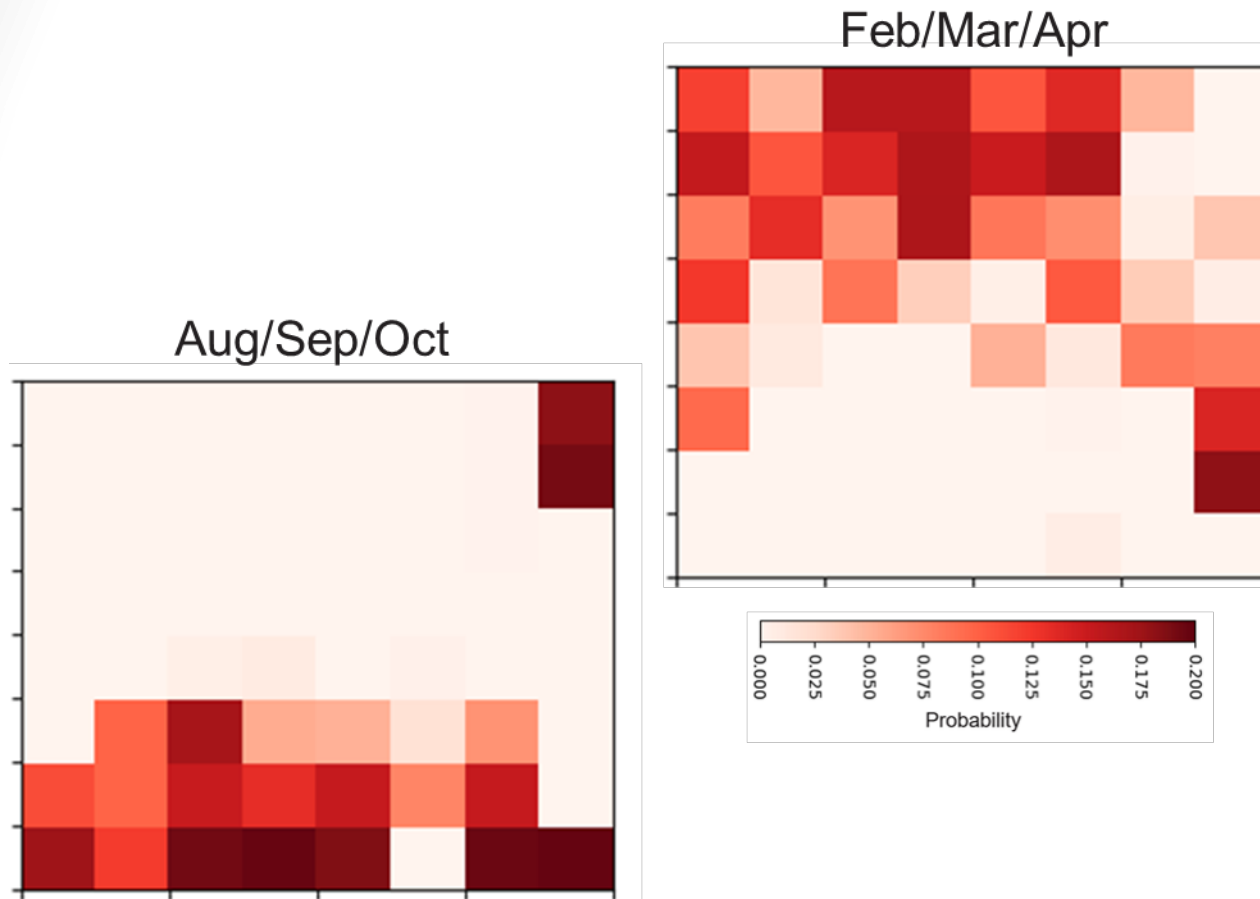




STOCHASTIC WEATHER GENERATOR – PROBABILITIES

Efficient time-continuous met-ocean conditions

1. Identify common weather patterns.
2. Retain transitional and persistence probabilities.



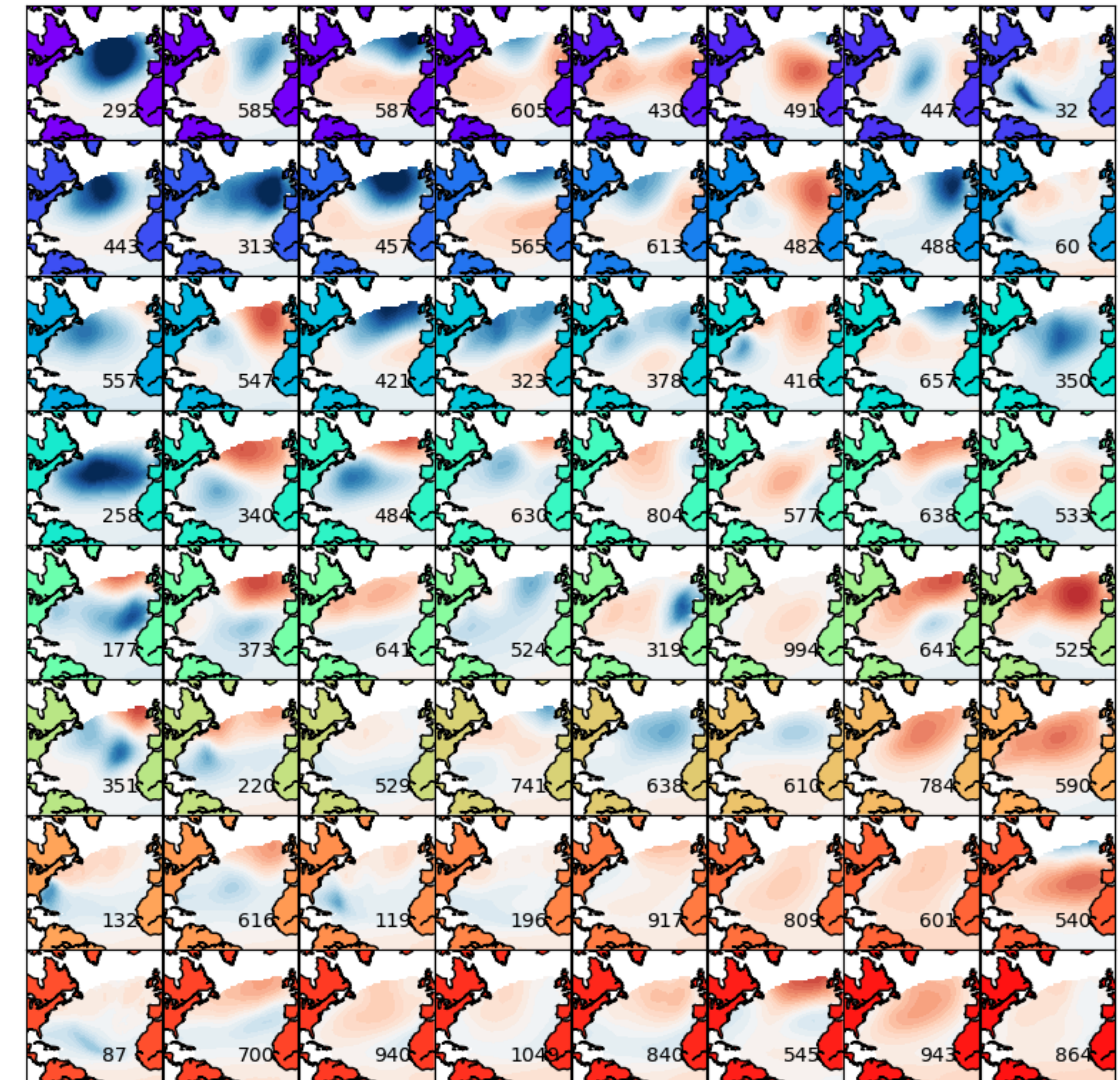
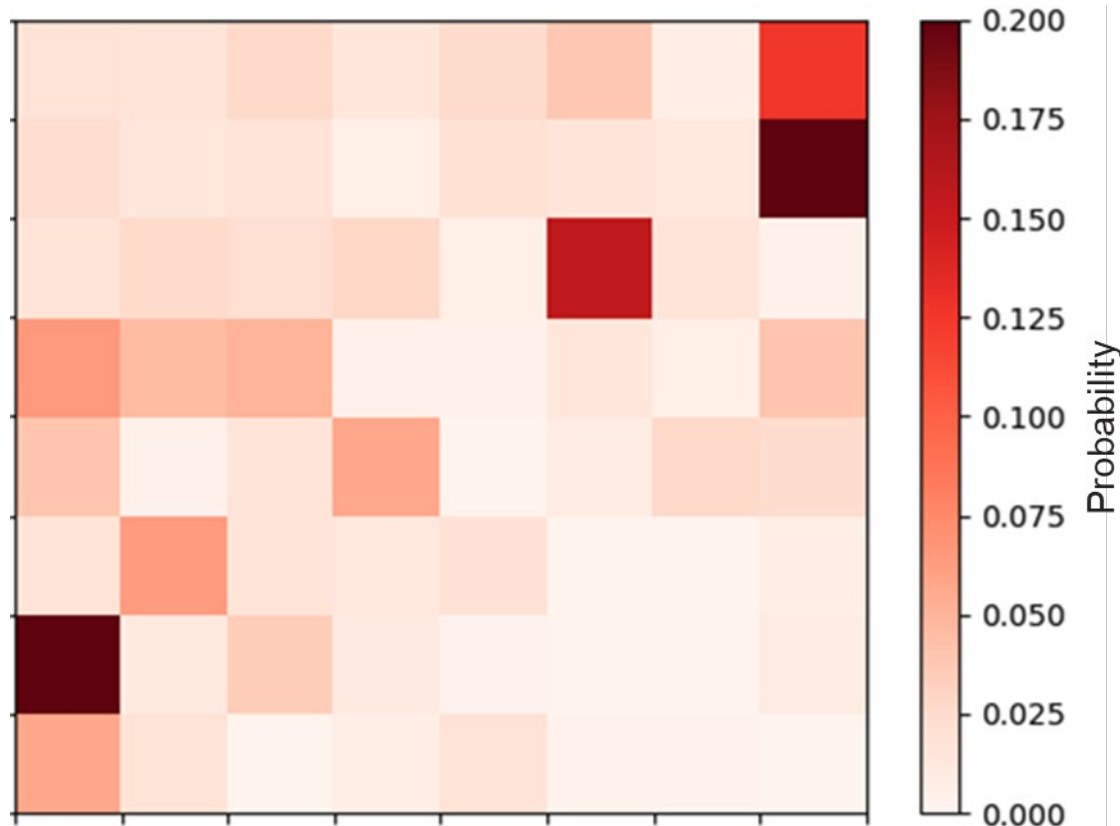


STOCHASTIC WEATHER GENERATOR – STORM PROBABILITY

Efficient time-continuous met-ocean conditions

1. Identify common weather patterns

Probability of Storms: 12-hour SLP pattern
with 8+ hours of waves exceeding H_{95} , ~2.5 m.





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STOCHASTIC WEATHER GENERATOR – STORMY WEATHER PATTERNS



Efficient time-continuous met-ocean conditions

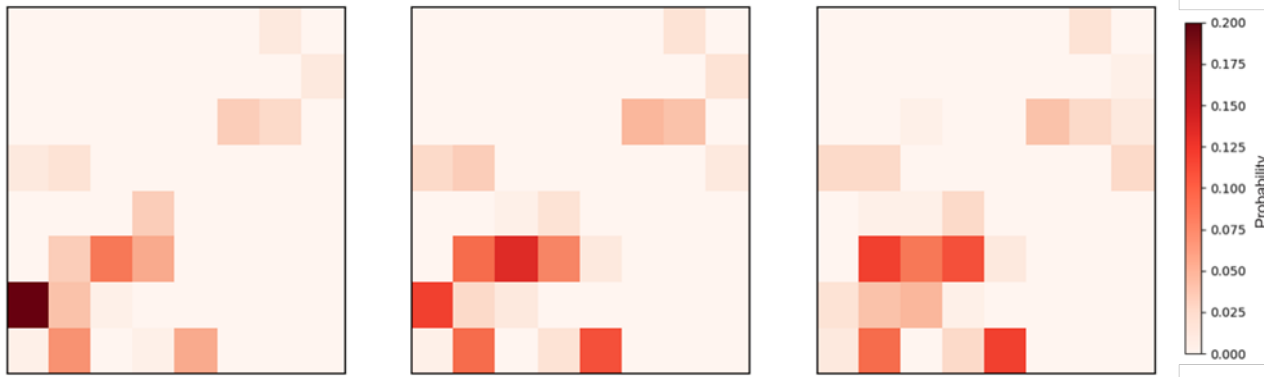
1. Identify common weather patterns.
2. Retain transitional and persistence probabilities.

Transition matrix following 'stormy' weather pattern:

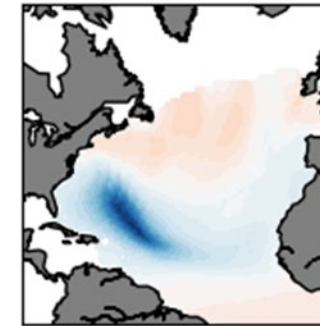
1-day later

2-days later

3-days later

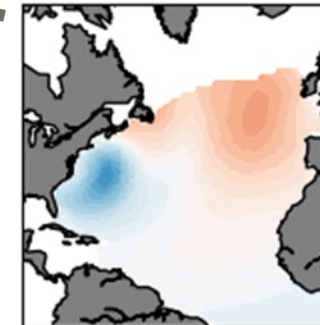


Markov Chain probabilities can efficiently train the sequencing of events (seconds on a laptop).



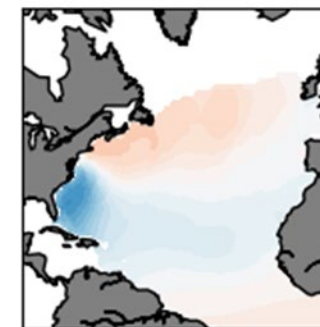
West
Atlantic
Hurricanes

Jan Mar May Jul Sep Nov



Nor'easters

Jan Mar May Jul Sep Nov



Hurricanes
originating in the
Gulf of Mexico

Jan Mar May Jul Sep Nov

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STOCHASTIC WEATHER GENERATOR – EXTERNAL CAUSES OF STOCHASTICITY

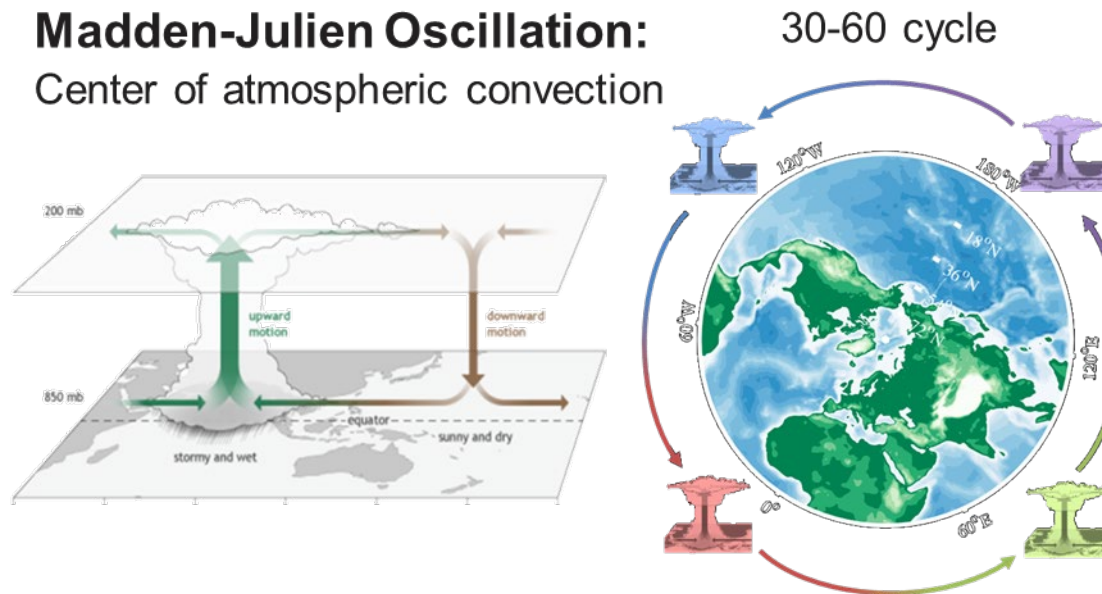
Efficient time-continuous met-ocean conditions

1. Identify common weather patterns.
2. Retain transitional and persistence probabilities.
3. Define external causes of stochasticity.

Identifying large-scale climate processes that alter local weather occurrence probabilities:

Madden-Julien Oscillation:

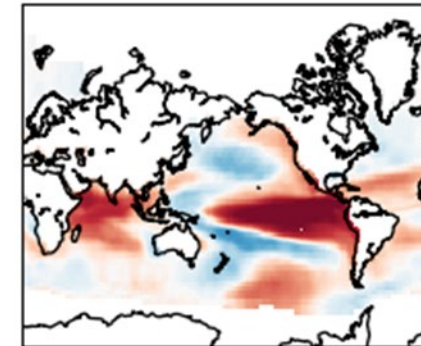
Center of atmospheric convection



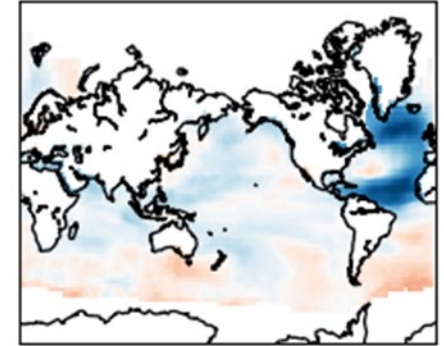
Sea Surface Temperatures:

- El Nino Southern Oscillation (ENSO)
- Atlantic Multidecadal Oscillation (AMO)
- Pacific Decadal Oscillation (PDO)
- Southern Index Oscillation (SOI)

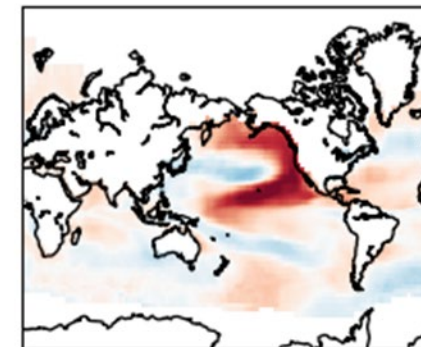
Rotated EOF #1



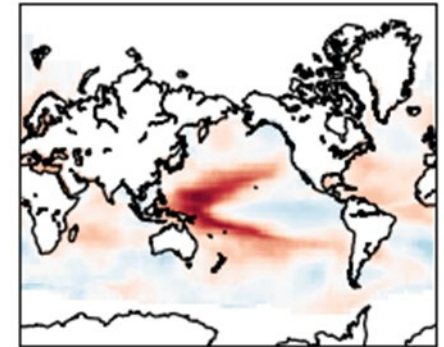
Rotated EOF #3



Rotated EOF #2



Rotated EOF #4

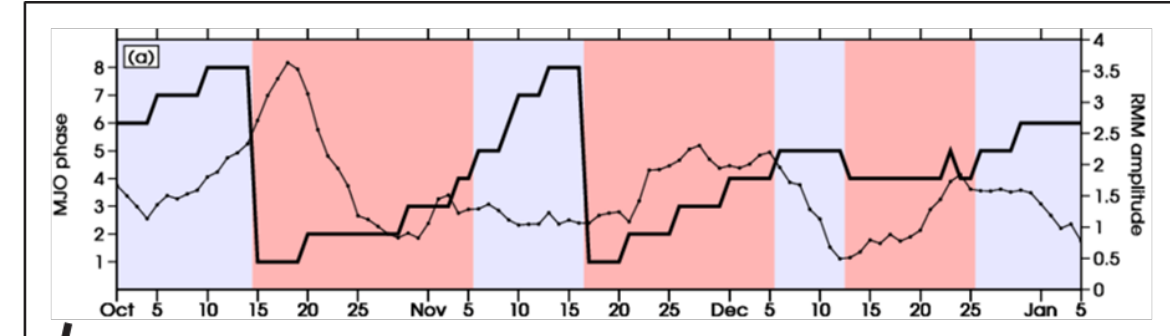




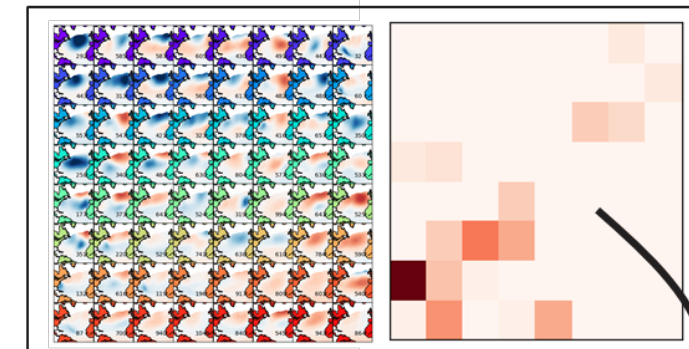
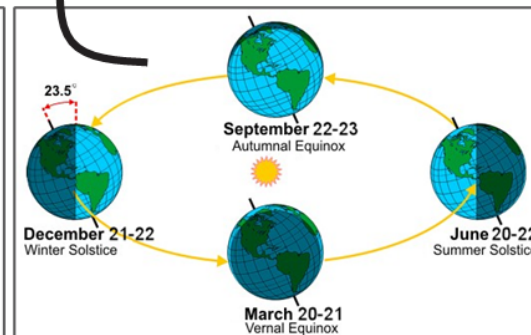
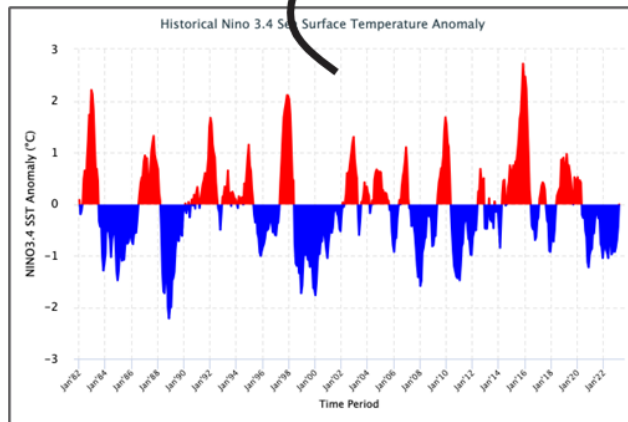
STOCHASTIC WEATHER GENERATOR – AUTO-LOGISTIC REGRESSION MODEL

Efficient time-continuous met-ocean conditions

1. Identify common weather patterns.
2. Retain transitional and persistence probabilities.
3. Define external causes of stochasticity.
4. Auto-Logistic Regression Model



$$\mathbf{X}_t = \left\{ \overbrace{X_{1,t}^a, X_{2,t}^a, X_{3,t}^a}^{\text{Interannual}}, \overbrace{\cos \frac{2\pi t}{T_a}, \sin \frac{2\pi t}{T_a}}^{\text{Seasonal}}, \overbrace{X_{1,t}^{MJO}, X_{2,t}^{MJO}}^{\text{Sub-monthly}} \right\}$$



$$Pr(DWT_t = i) | DWT_{t-1}, \dots, DWT_{t-e}, X_t^a, X_t^m, X_t^{MJO} = \frac{\exp\left(\alpha_i + \beta_i X_t + \sum_{j=1}^e \gamma_{ij} DWT_{t-j}^d\right)}{\sum_{k=1}^{n_{DWT}} \left(\alpha_k + \beta_k X_t + \underbrace{\sum_{j=1}^e \gamma_{kj} DWT_{t-j}^d}_{\text{Daily}}\right)}; \forall i, \dots, n_{DWT}$$

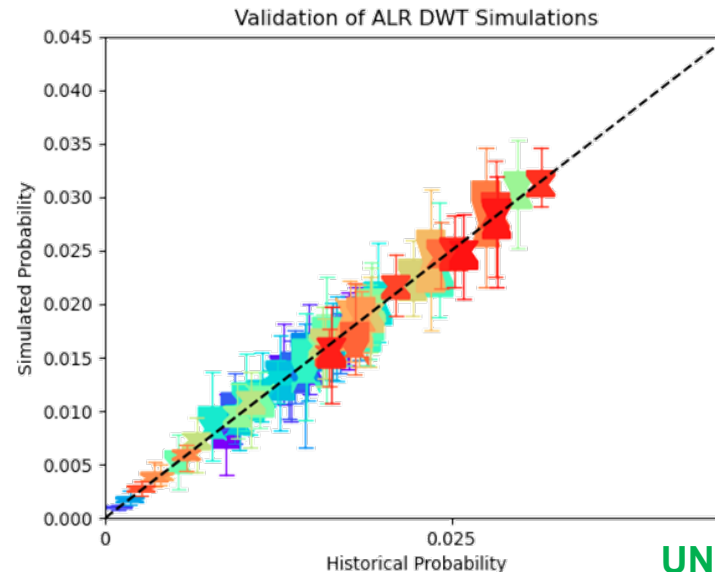
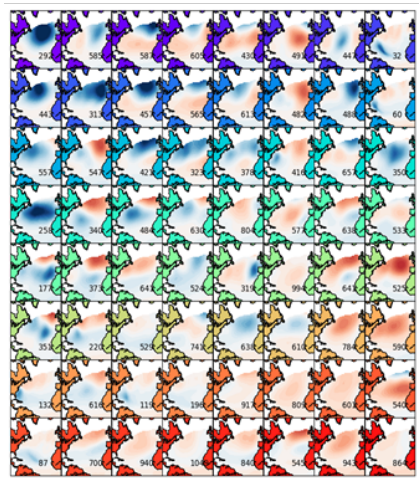
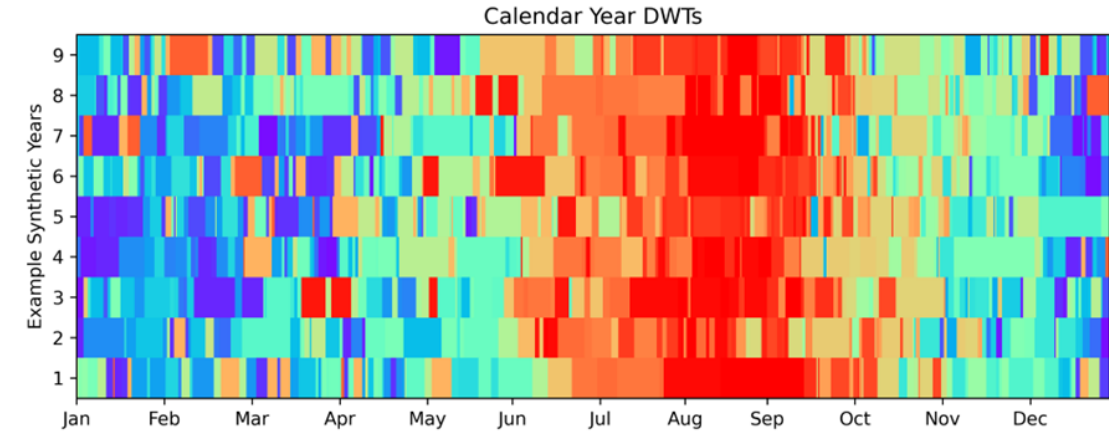


STOCHASTIC WEATHER GENERATOR – AUTO-LOGISTIC REGRESSION MODEL, CONT.

Efficient time-continuous met-ocean conditions

1. Identify common weather patterns.
2. Retain transitional and persistence probabilities.
3. Define external causes of stochasticity.
4. Auto-Logistic Regression Model

$$\mathbf{X}_t = \left\{ \overbrace{X_{1,t}^a, X_{2,t}^a, X_{3,t}^a}^{\text{Interannual}}, \overbrace{\cos \frac{2\pi t}{T_a}, \sin \frac{2\pi t}{T_a}}^{\text{Seasonal}}, \overbrace{X_{1,t}^{MJO}, X_{2,t}^{MJO}}^{\text{Sub-monthly}} \right\}$$



$$Pr(DWT_t = i) | DWT_{t-1}, \dots, DWT_{t-e}, X_t^a, X_t^m, X_t^{MJO} = \frac{\exp\left(\alpha_i + \beta_i X_t + \sum_{j=1}^e \gamma_{ij} DWT_{t-j}^d\right)}{\sum_{k=1}^{n_{DWT}} \left(\alpha_k + \beta_k X_t + \underbrace{\sum_{j=1}^e \gamma_{kj} DWT_{t-j}^d}_{\text{Daily}}\right)}; \forall i=1, \dots, n_{DWT}$$



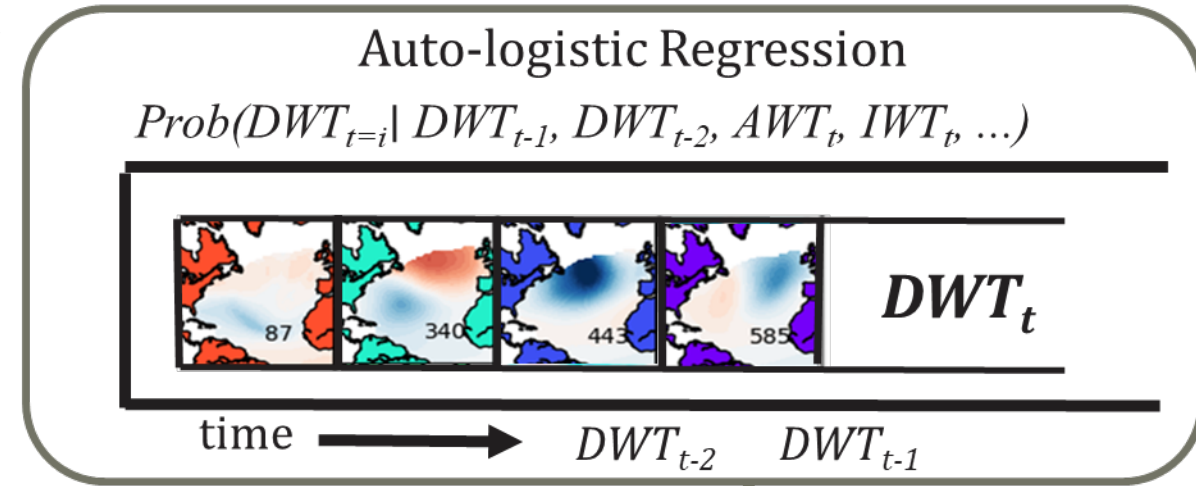
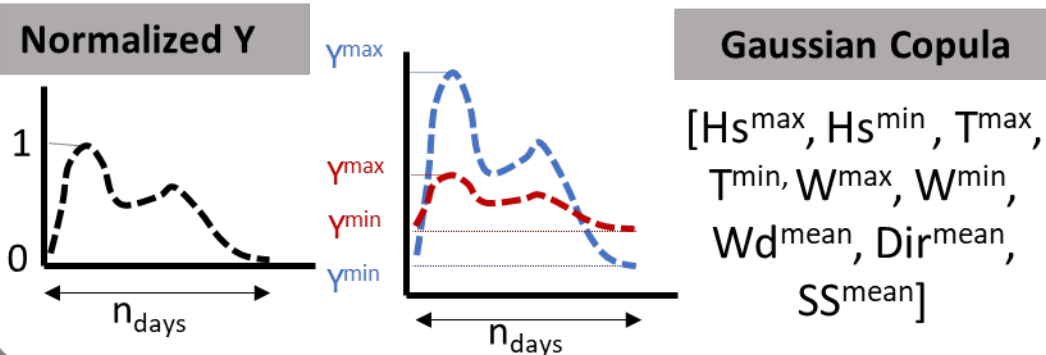
STOCHASTIC WEATHER GENERATOR – STATISTICAL DOWNSCALING

Efficient time-continuous met-ocean conditions

1. Identify common weather patterns.
2. Retain transitional and persistence probabilities.
3. Define external causes of stochasticity.
4. Auto-Logistic Regression Model
5. Statistical Downscaling

Cagigal et al. (2021): Extract ‘hydrographs’ from time series of historical behavior within each WT

Hydrograph Stitching Method



Simulated Time Series of Coastal Conditions (Y)

$Y_s(t)$

$\eta_A(t)$

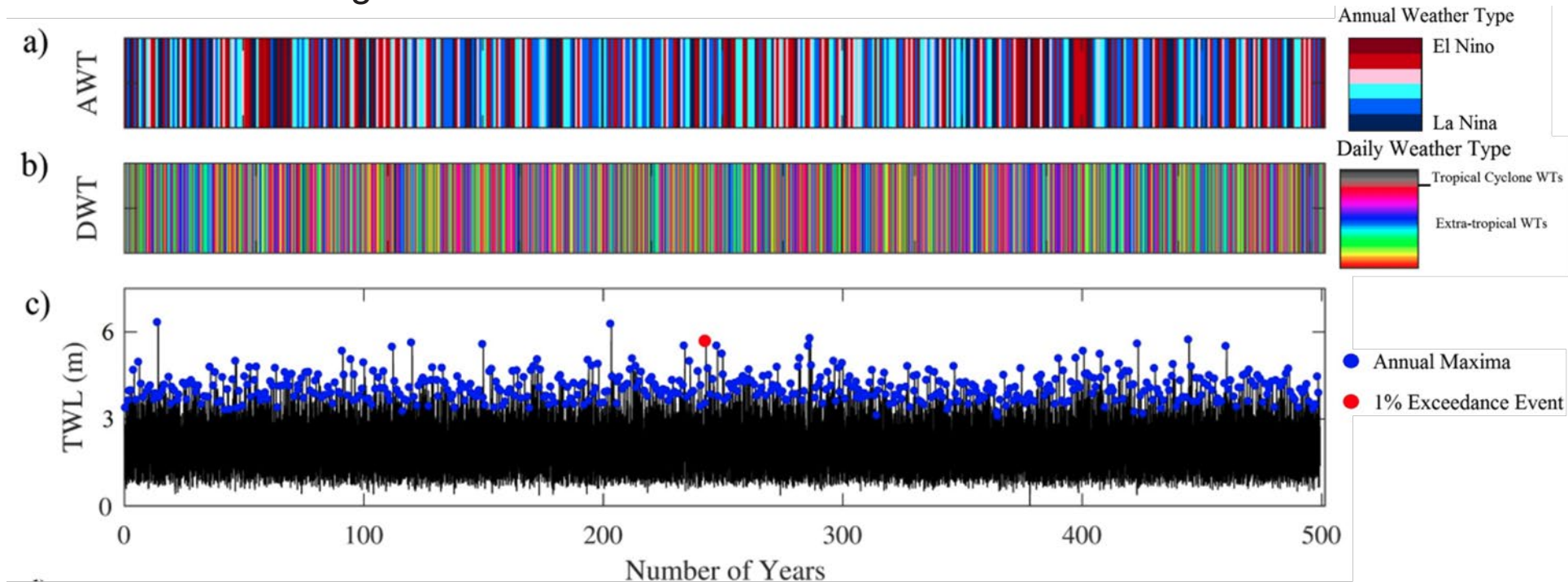




STOCHASTIC WEATHER GENERATOR – STATISTICAL DOWNSCALING, CONT.

Efficient time-continuous met-ocean conditions

1. Identify common weather patterns.
2. Retain transitional and persistence probabilities.
3. Define external causes of stochasticity.
4. Auto-Logistic Regression Model
5. Statistical Downscaling





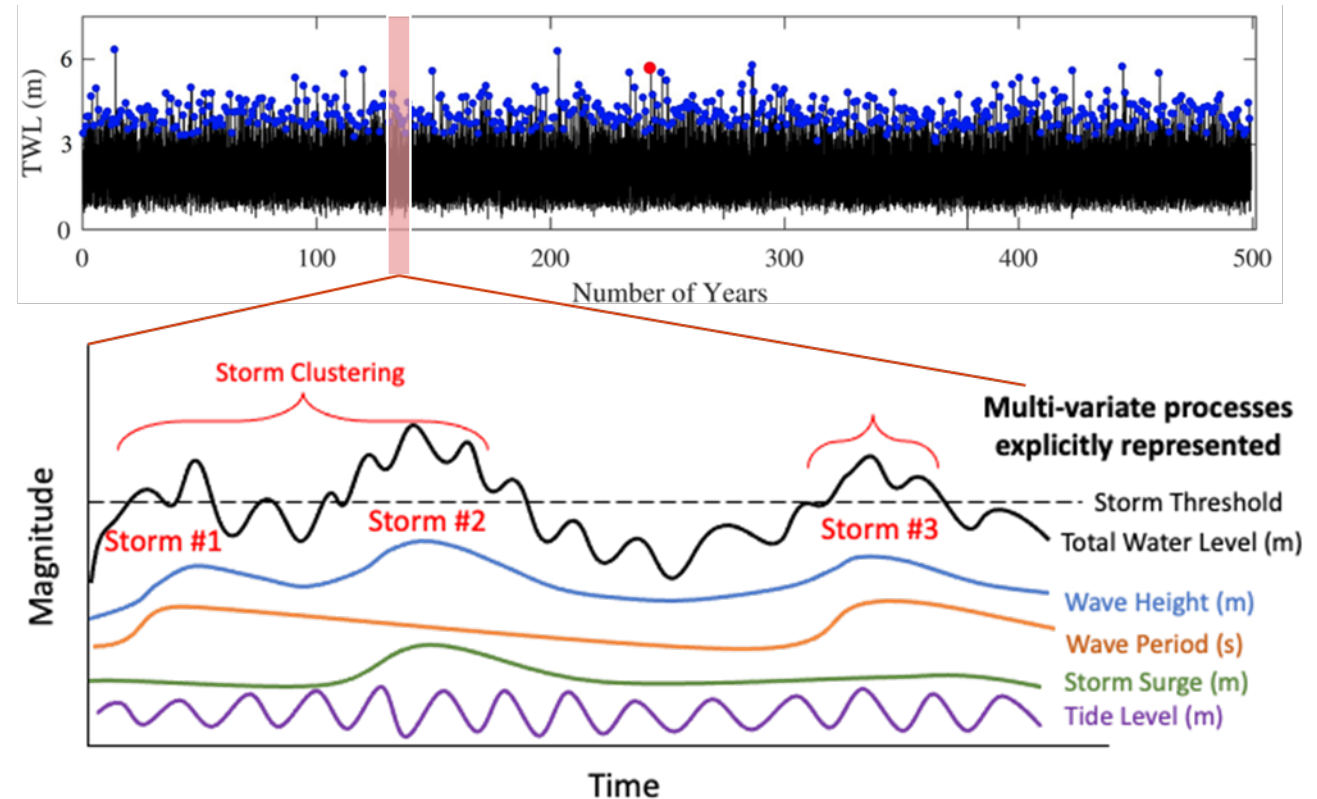
STOCHASTIC WEATHER GENERATOR – MODEL INPUT CONDITIONS

Efficient time-continuous met-ocean conditions

1. Identify common weather patterns.
2. Retain transitional and persistence probabilities.
3. Define external causes of stochasticity.
4. Auto-Logistic Regression Model
5. Statistical Downscaling
6. Model Input Conditions

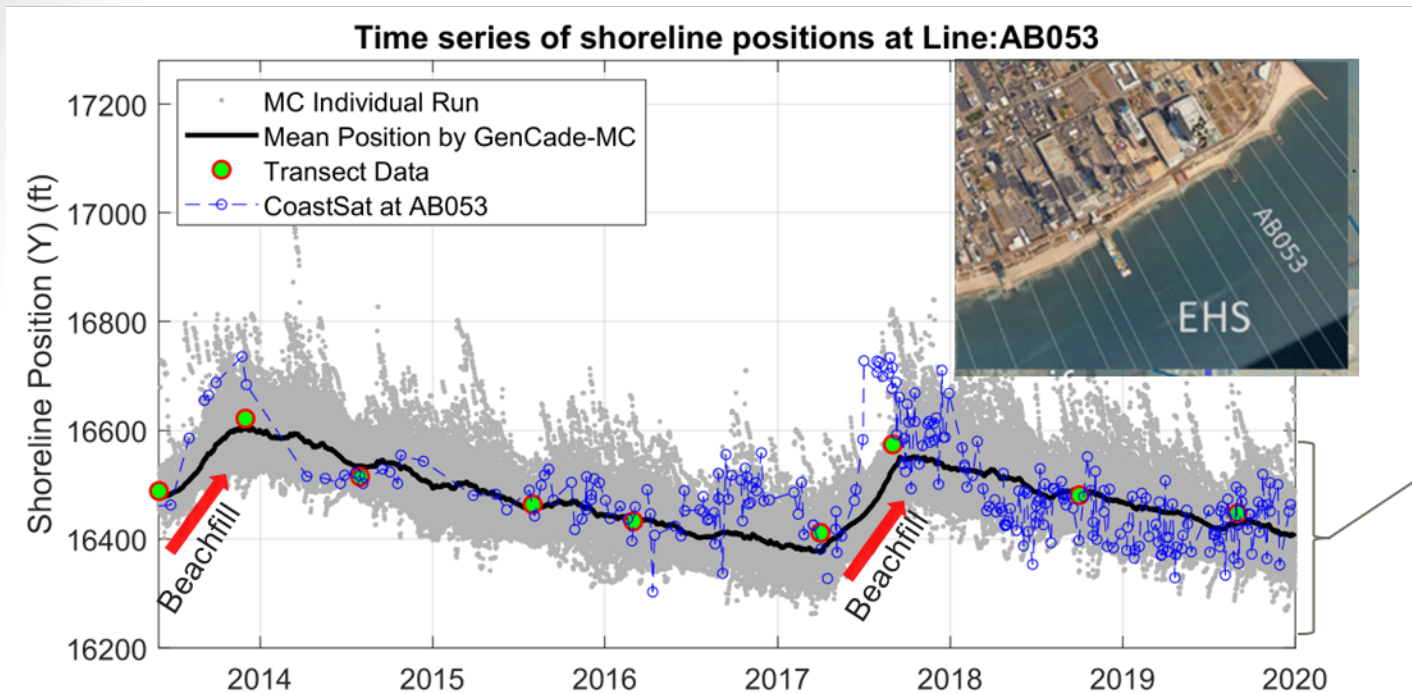
◆ **Direct estimation of multiple storm characteristics:**

- Magnitude, frequency, duration, timing, clustering, etc.
- **But also capture inter-storm meteorology and oceanographic forcings of recovery**
 - Distant swells, compounding still water levels, seasonality, etc.



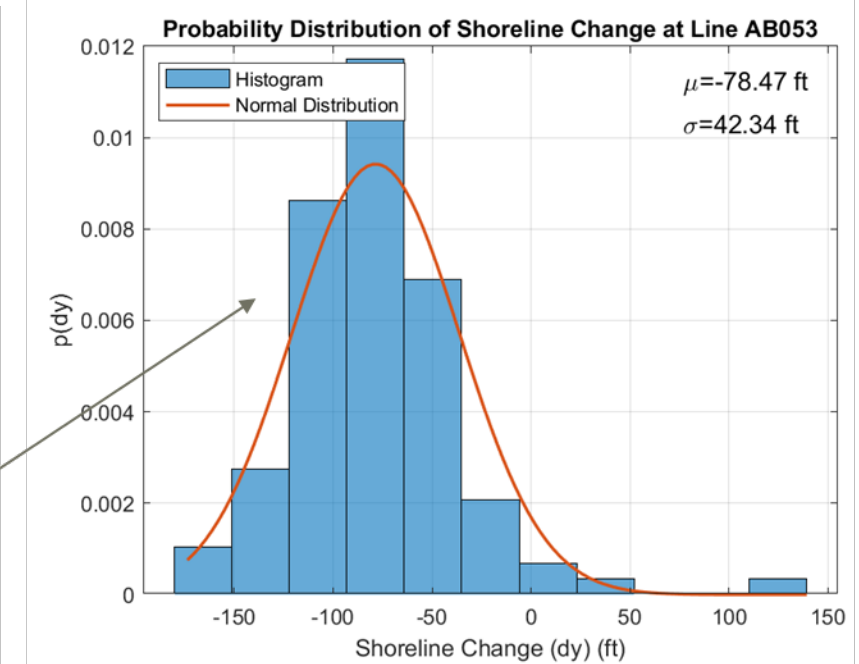


GENCADE MONTE-CARLO SIMULATIONS IN EHS ALONG ABSECON ISLAND, NJ



(a) Temporal variation of shoreline positions at NAP monitoring line: AB053, of which location is marked as "x" in the box at the upper right corner.

Data Type	Transects	CoastSat	Transect + CoastSat
N_0	770	12905	13675
σ_{max}^{obs} (ft)	106.771	190.498	190.498
L_σ	0.835	0.738	0.748



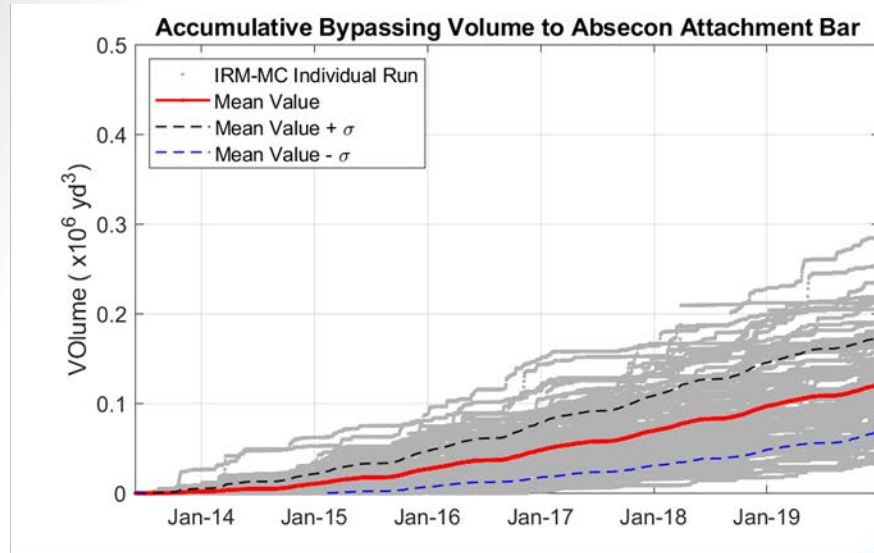
(b) Probability density function of shoreline change at the end of simulation, 12/31/2019. The initial shoreline is on 05/31/2013. μ = mean of the changes; σ =standard deviation

Likelihood Value:

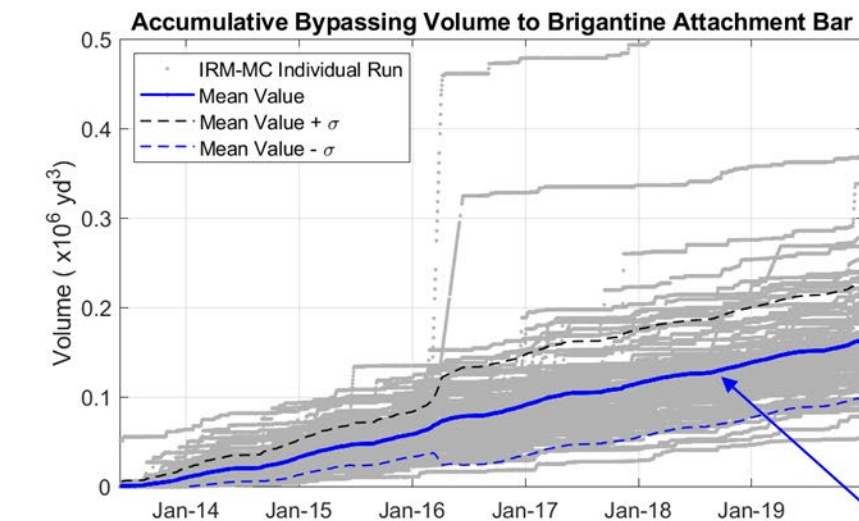
$$L_\sigma = \frac{1}{N_s} \sum_j \exp \left(-\frac{1}{N_0} \sum_k \left(\frac{y_k^{N_0} - y_{k,j}^{N_s}}{\sigma_{max}^{obs}} \right)^2 \right)$$



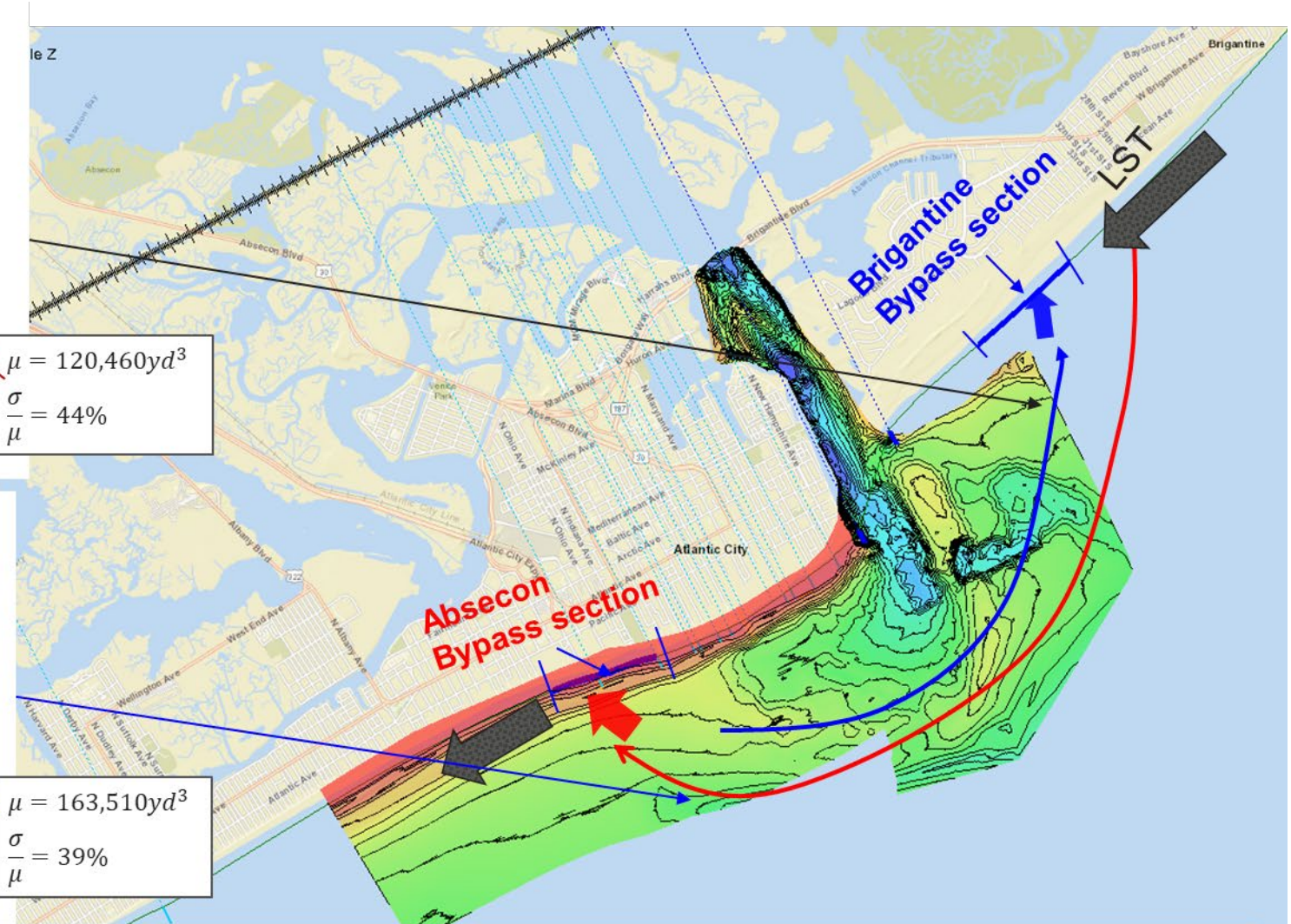
UNCERTAINTY OF INLET BYPASSING VOLUMES ESTIMATED BY GENCADE-IRM MONTE-CARLO



$$\mu = 120,460 \text{ yd}^3$$
$$\frac{\sigma}{\mu} = 44\%$$



$$\mu = 163,510 \text{ yd}^3$$
$$\frac{\sigma}{\mu} = 39\%$$



- Annual bypassing rate is about 10 ~15 % of Annual LST rate (200 ~ 300k yd³/year)



COUPLING WITH THE DUNE RESPONSE TOOL

Published March 2025:

Earth's Future

RESEARCH ARTICLE

10.1029/2024EF005335

Key Points:

- A stochastic weather emulator is used to force a fast coastal foredune evolution model to predict dune stability.

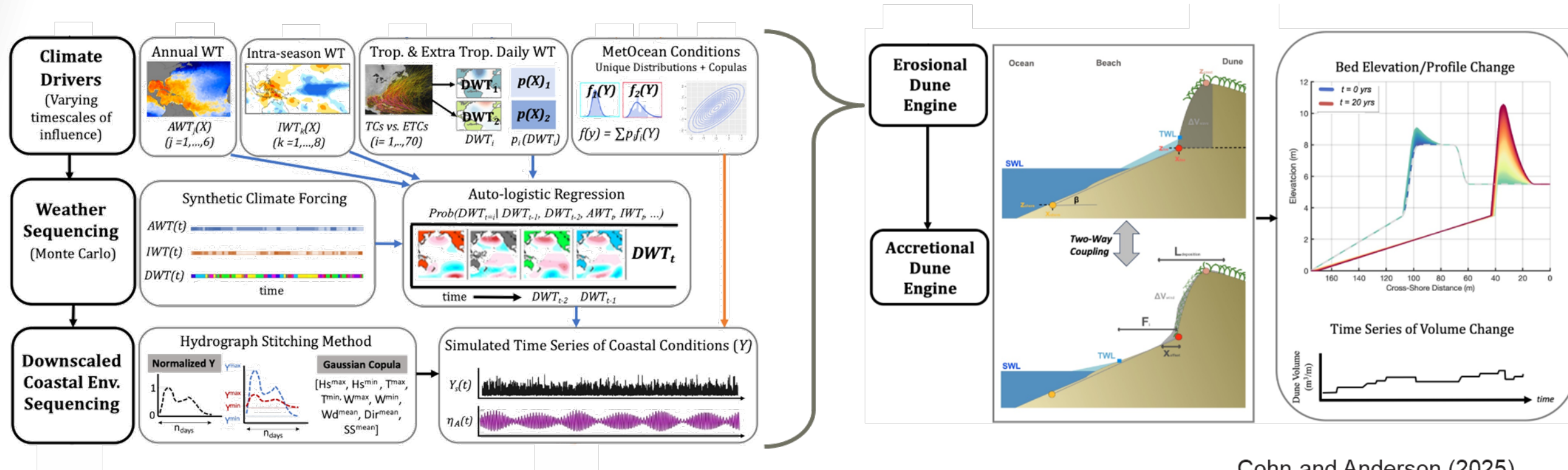
Projecting the Longevity of Coastal Foredunes Under Stochastic Meteorological and Oceanographic Forcing

Nicholas Cohn¹ and Dylan Anderson¹

¹Coastal and Hydraulics Laboratory—Field Research Facility, U.S. Army Engineer Research and Development Center, Duck, NC, USA



1000 synthetic chronologies of waves and winds was used to force the **Dune Response Tool**, an empirical dune evolution model to quantify potential dune volume change:

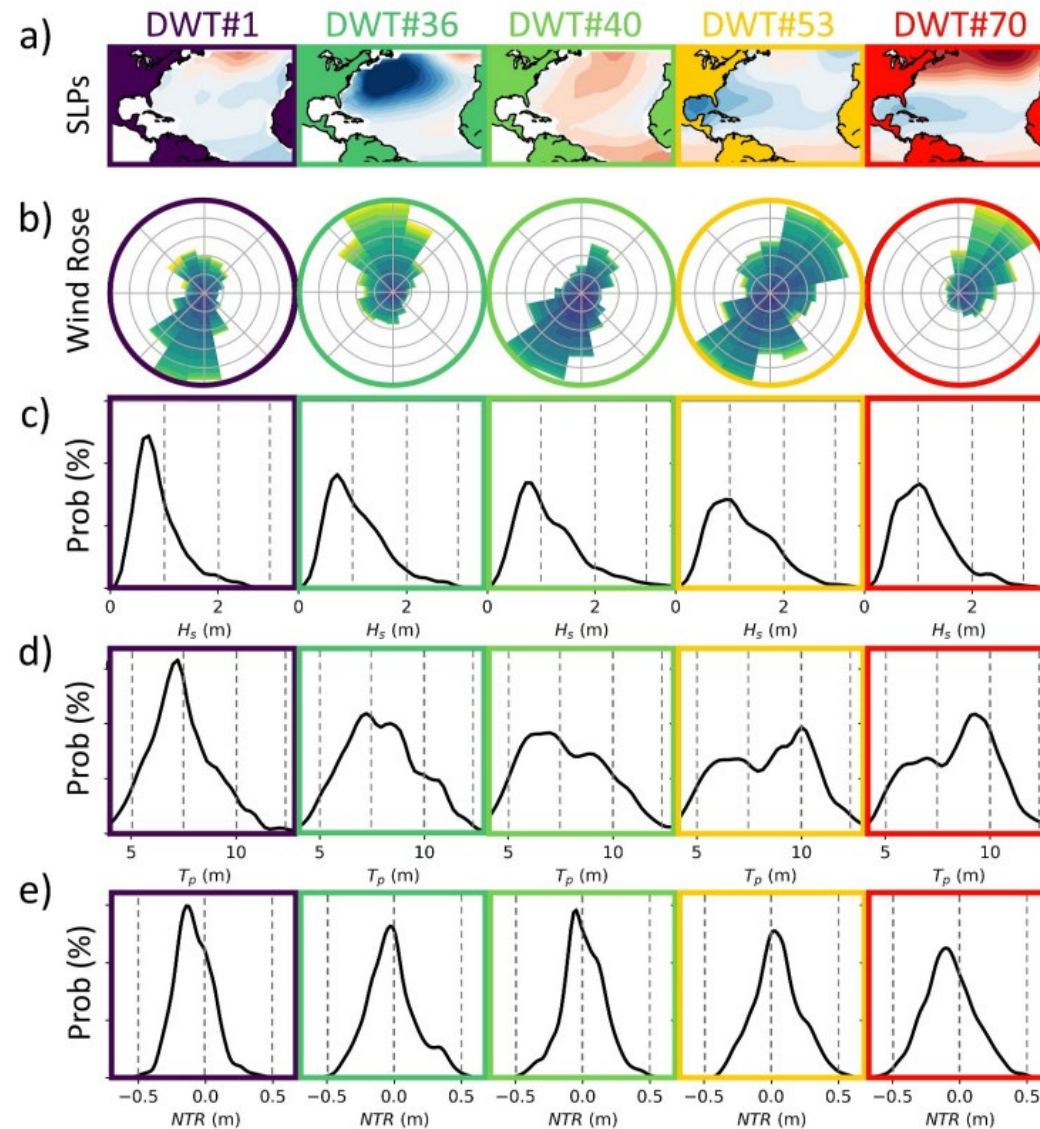


Cohn and Anderson (2025)



UNCLASSIFIED

DAILY WEATHER TYPES



UNCLASSIFIED



DUNE RESPONSE TOOL RESULTS

Quantifying the range of potential outcomes, including dune life-cycles and shoreline recession.

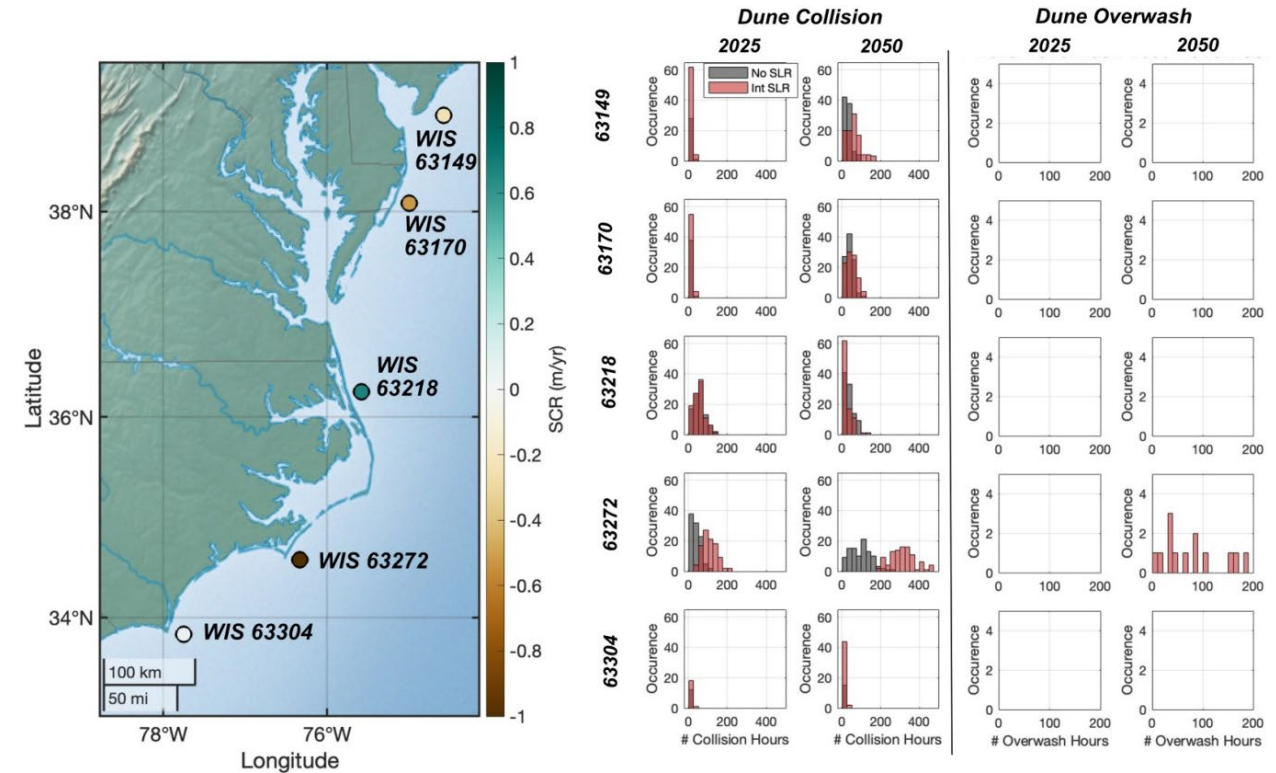
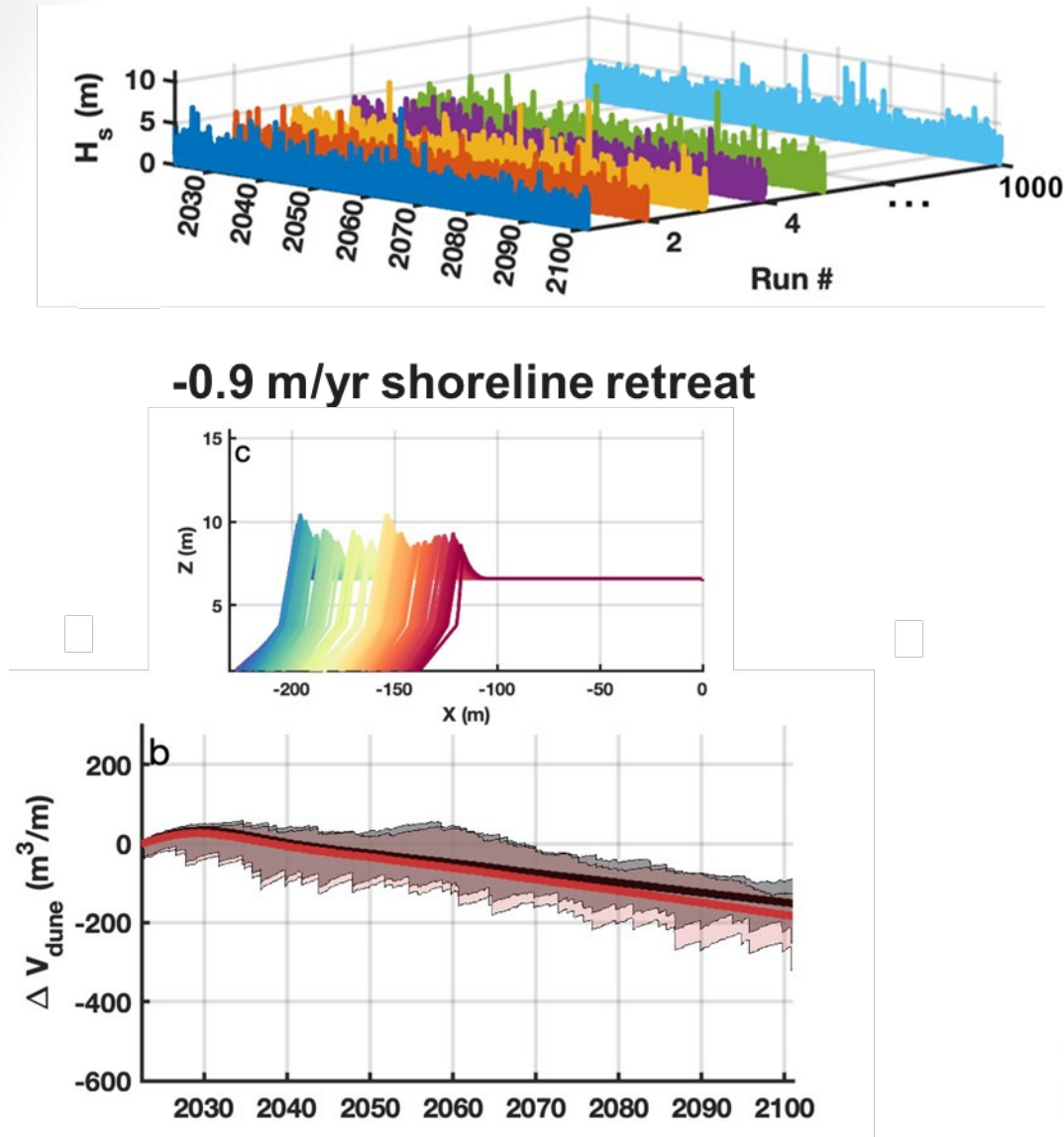


Figure 13. Map of five select regional demonstration locations, along with probability distributions of the number of dune collision hours and number of overwash predicted hours predicted by the model in years 2025 and 2050 for 100 TESLA cases simulated with and without SLR.



Not just limited to extremes: moderate processing like nuisance flooding too



Dr. Matthew Brand (LSU) Hybrid Marsh Restoration: changes in tidal amplitudes with restoration + SLR

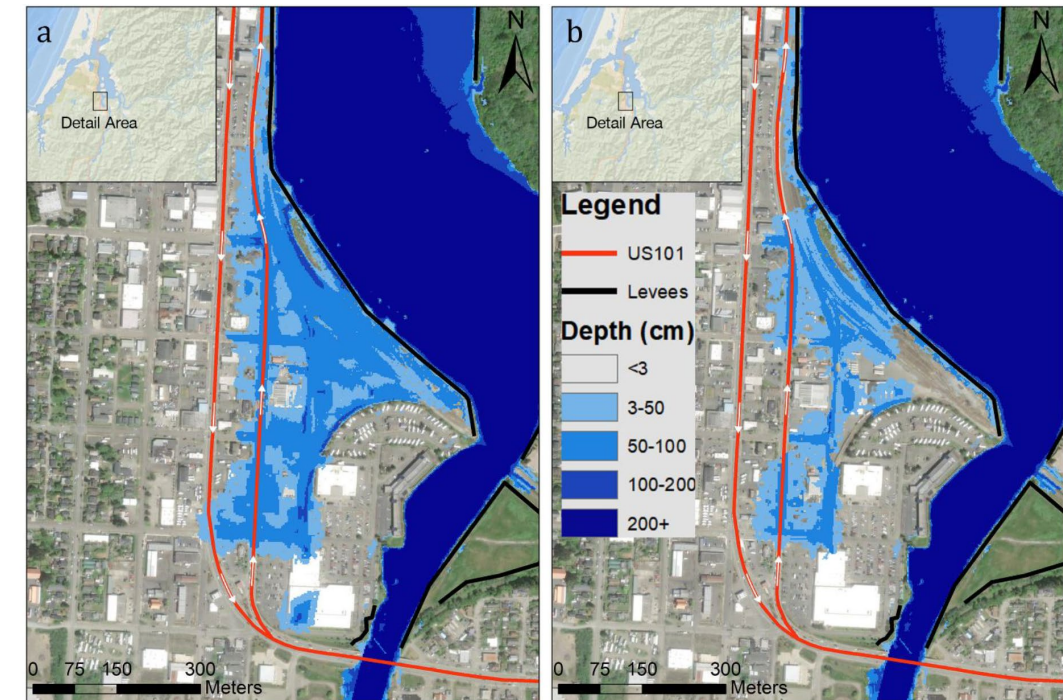
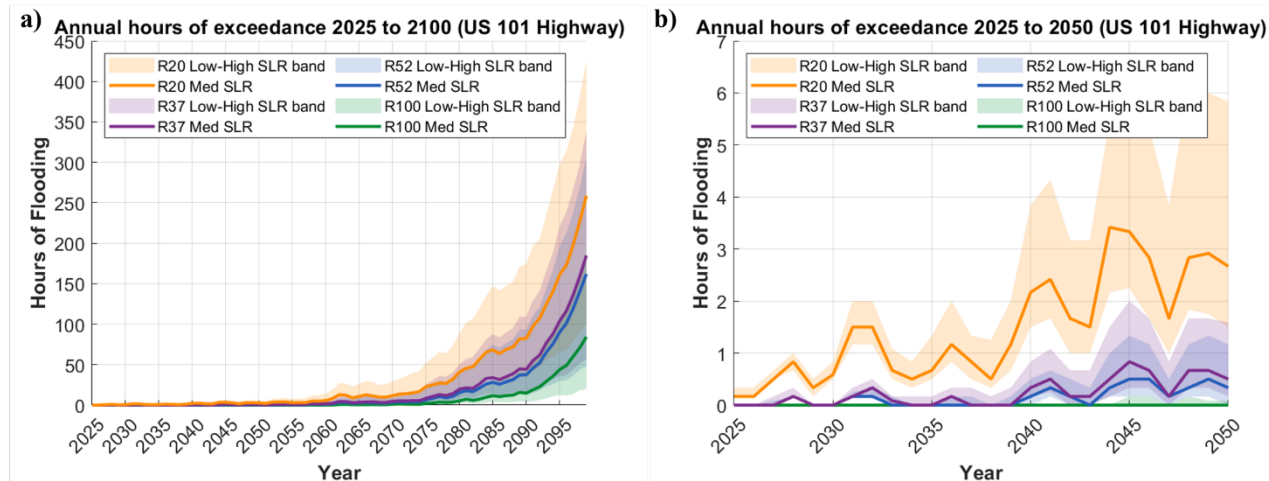
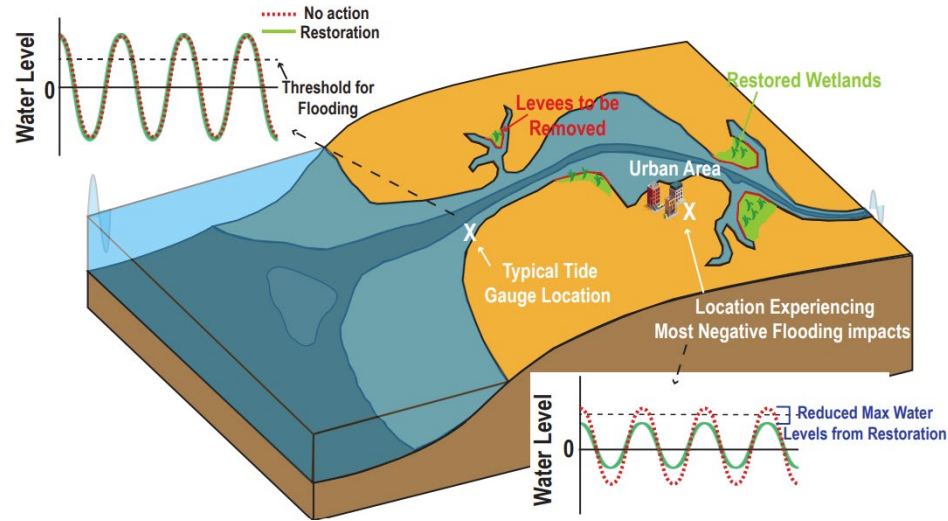
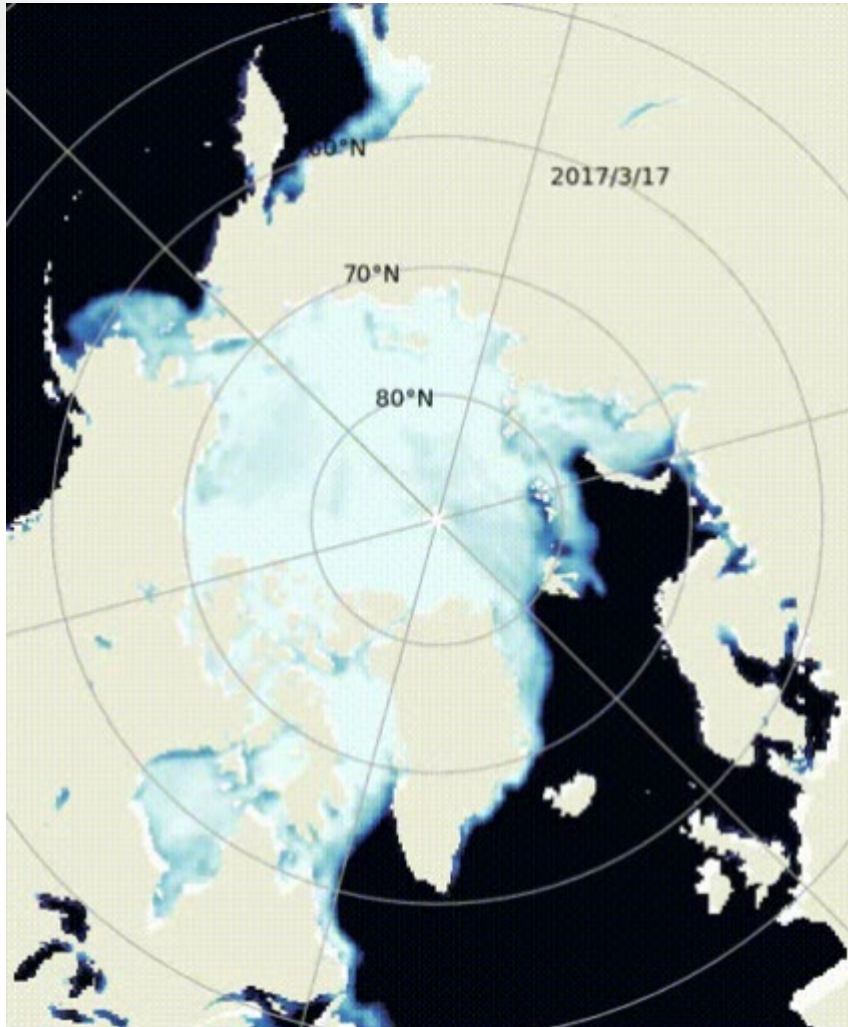


Figure 7. Modeled areal extent of flooding (depth in cm) along US Highway 101 (red lines) and in downtown Coos Bay under the median (82 cm) SLR scenario for the year 2100 for (a) the no-restoration (R0) scenario and (b) the 100% (R100) restoration scenario. White arrows show the direction of traffic along US 101.

Brand et al. (2025)

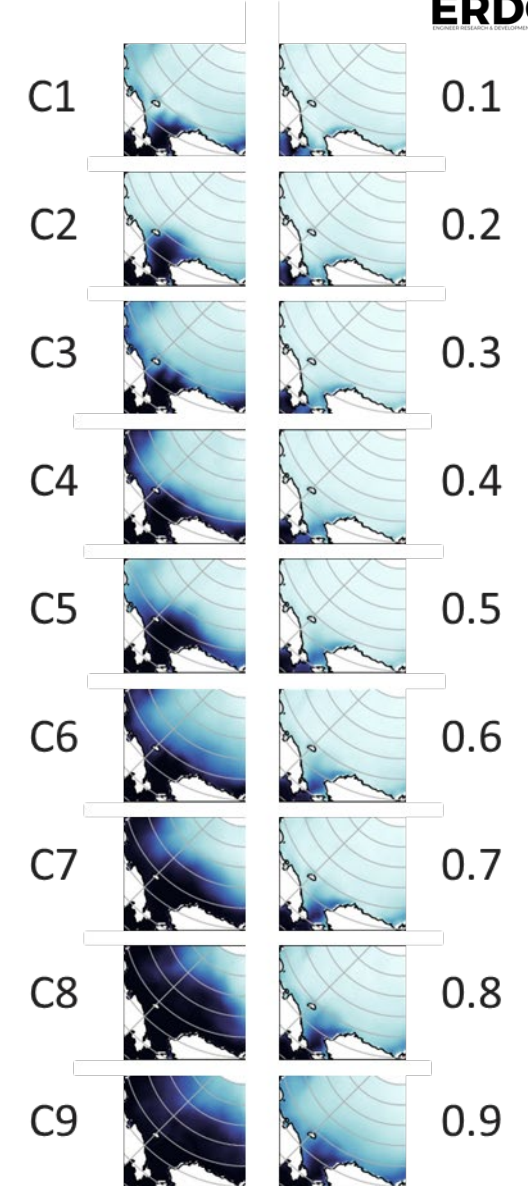
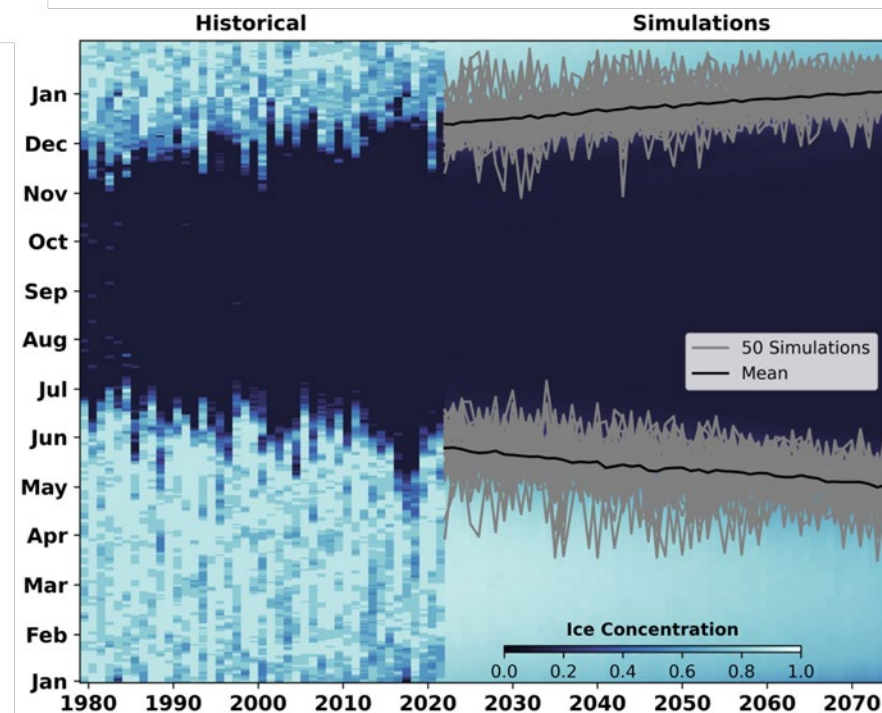


PROBABILISTIC PERMAFROST RETREAT



May et al. (2023) “*Stochastic Modeling of Sea Ice Concentration*”

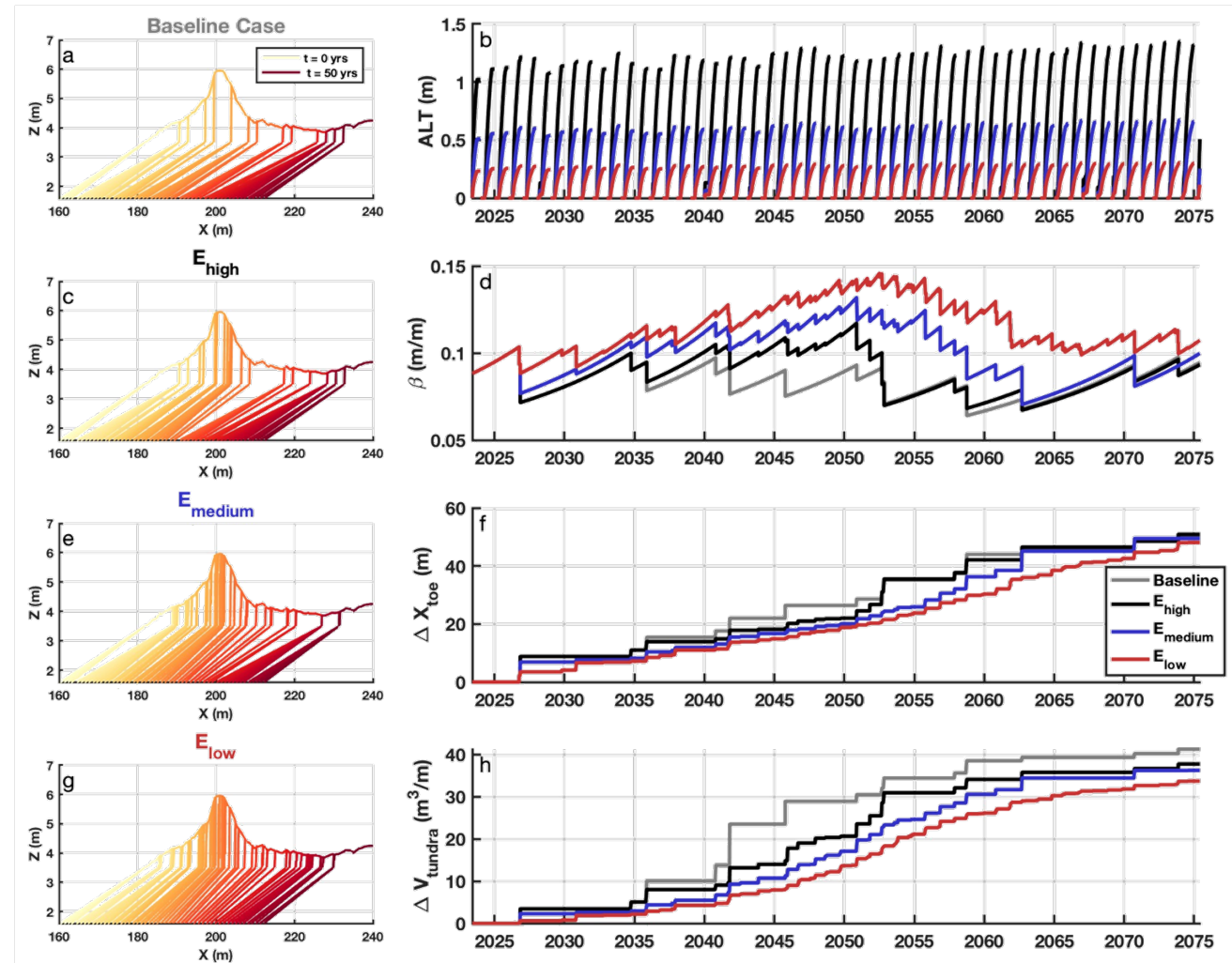
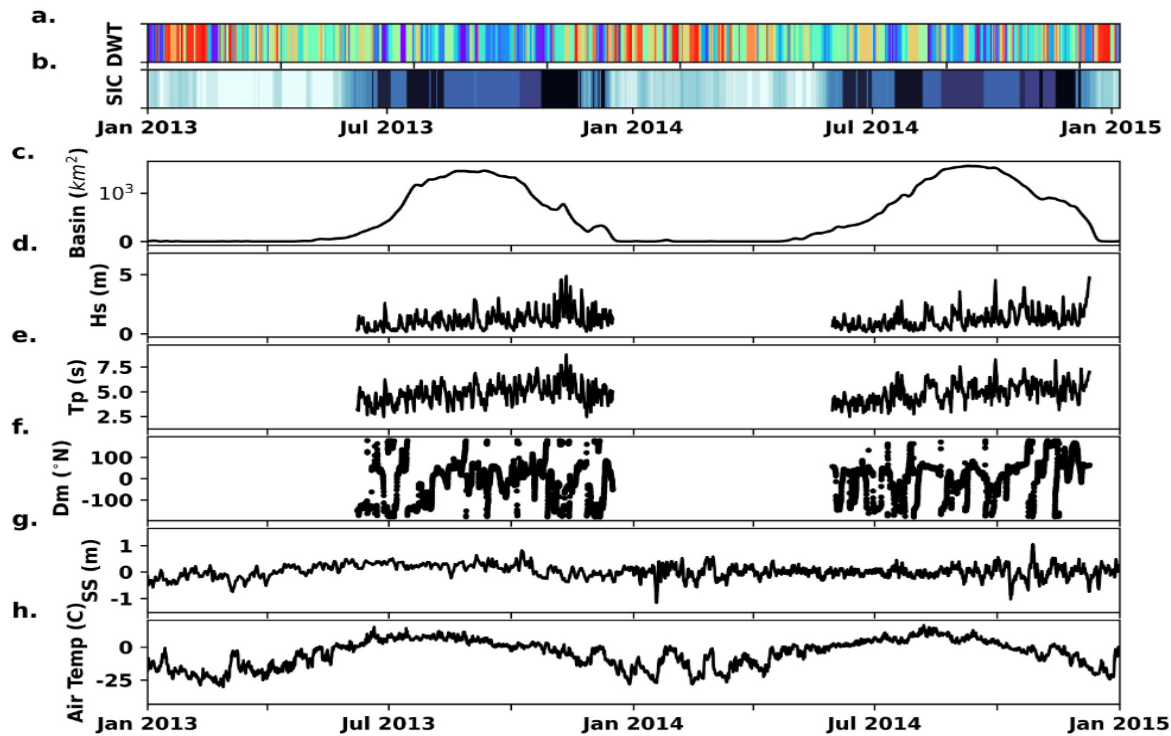
- Create a distribution of “wave basin sizes” unique to each cluster



Anderson and Cohn (2025)

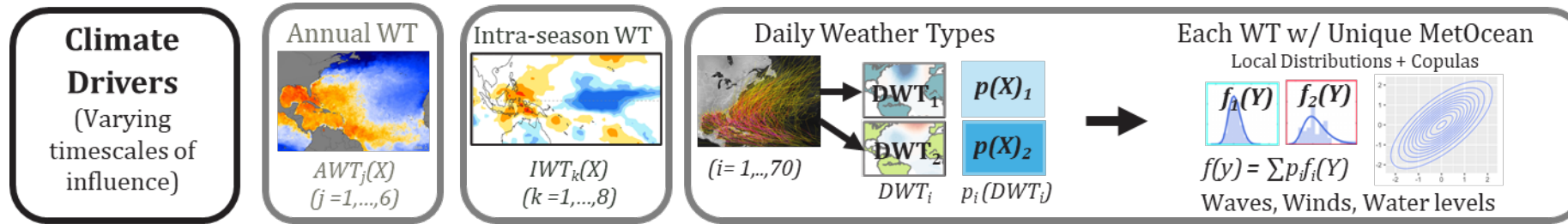


PERMAFROST RETREAT ANALYSIS

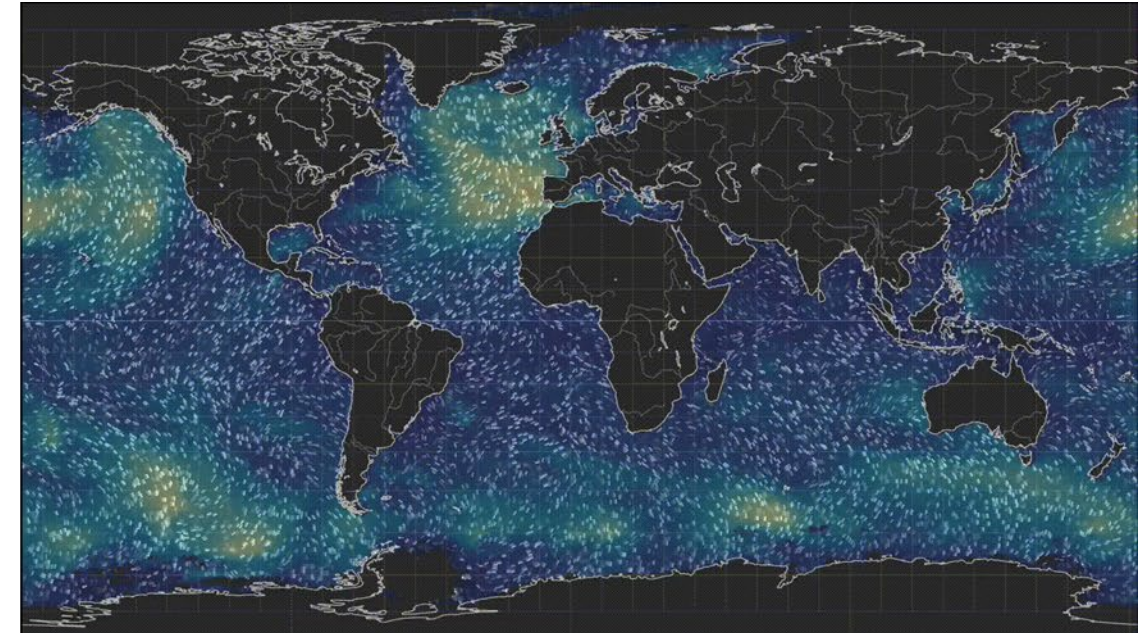
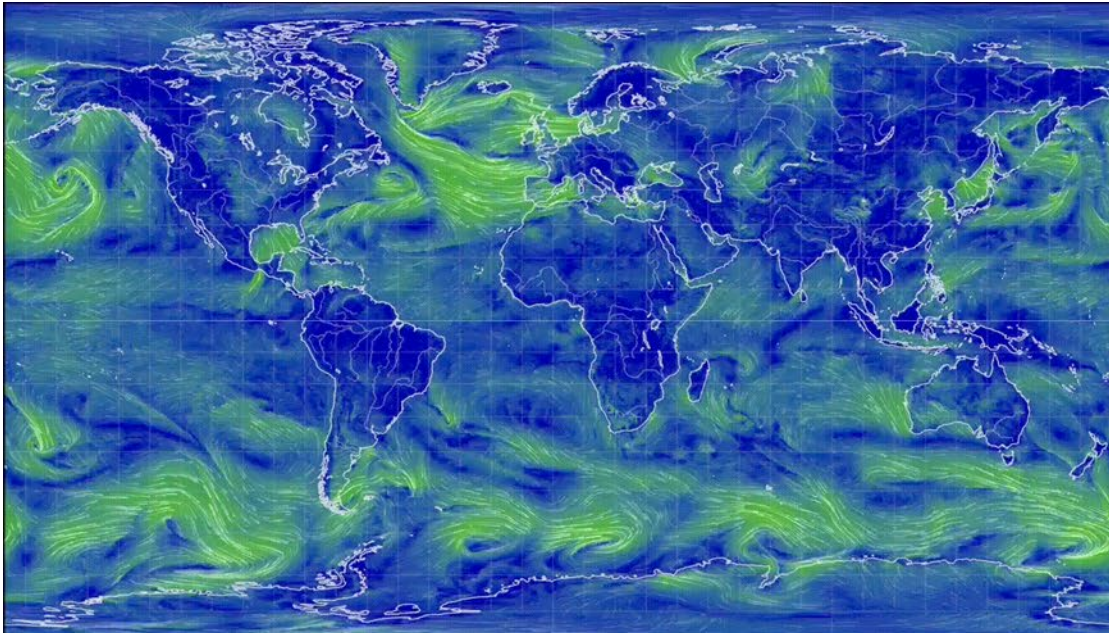




WORKING ON THE NEXT VERSION

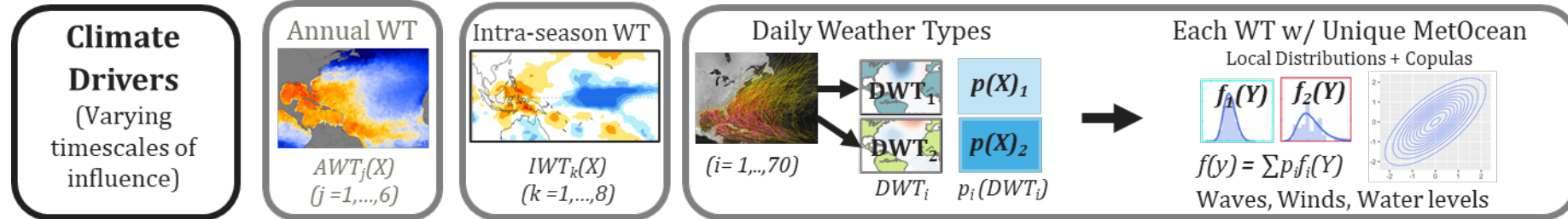


A conceptual limitation of this framework: *You have only seen the variance created in the historical record.*



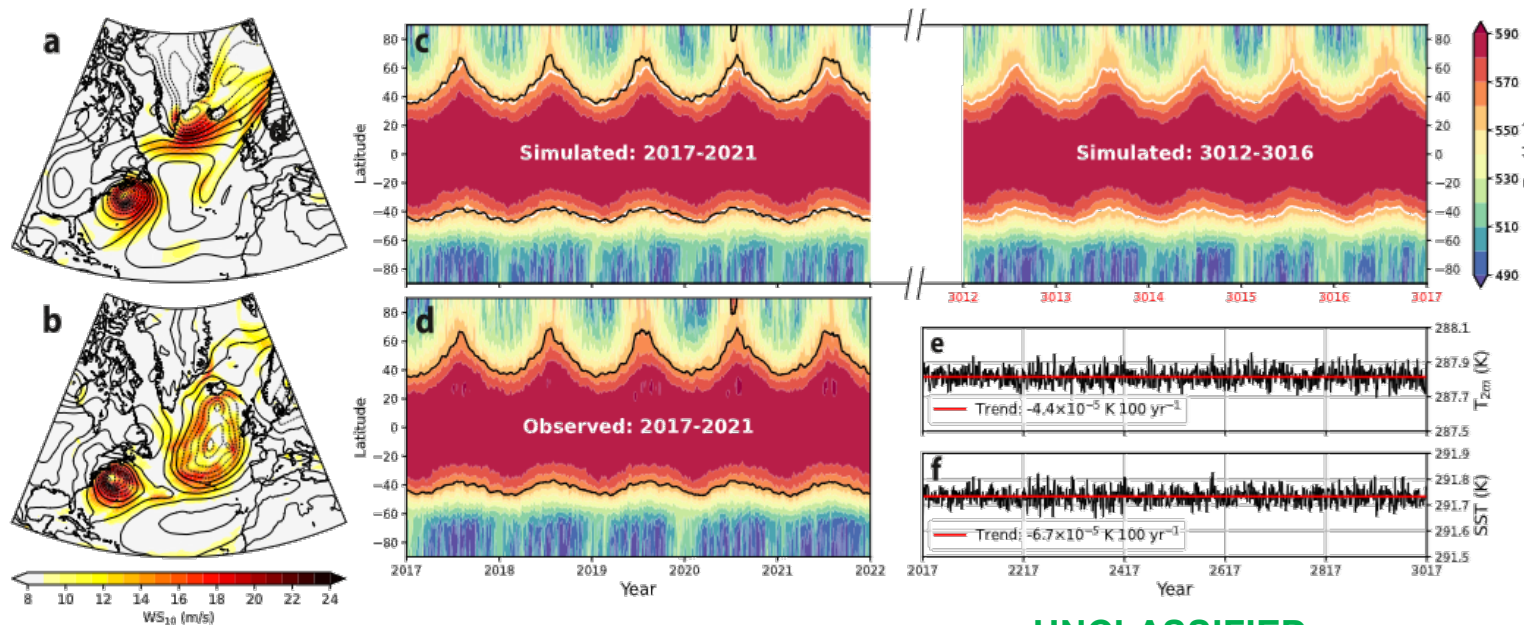


WORKING WITH ERDC'S WEATHER EFFECTS TEAM



A conceptual limitation of this framework: *You have only seen the variance created in the historical record.* But ML-enabled weather models can now simulate much more variance than the ~45 years of satellite observations:

A Deep Learning Earth System Model for Efficient Simulation of the Observed Climate (Cresswell & Clay, 2025)

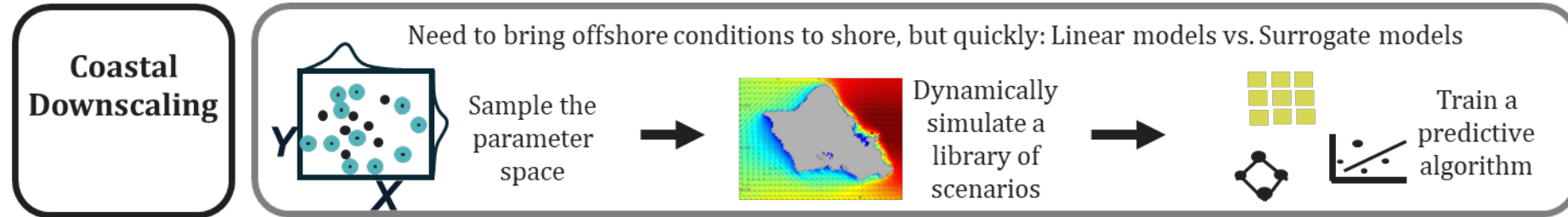


Working with ERDC's
Weather Effects Team:

Ted Letcher, Brendan West,
Sylvia Garmong, and Sandra LeGrand

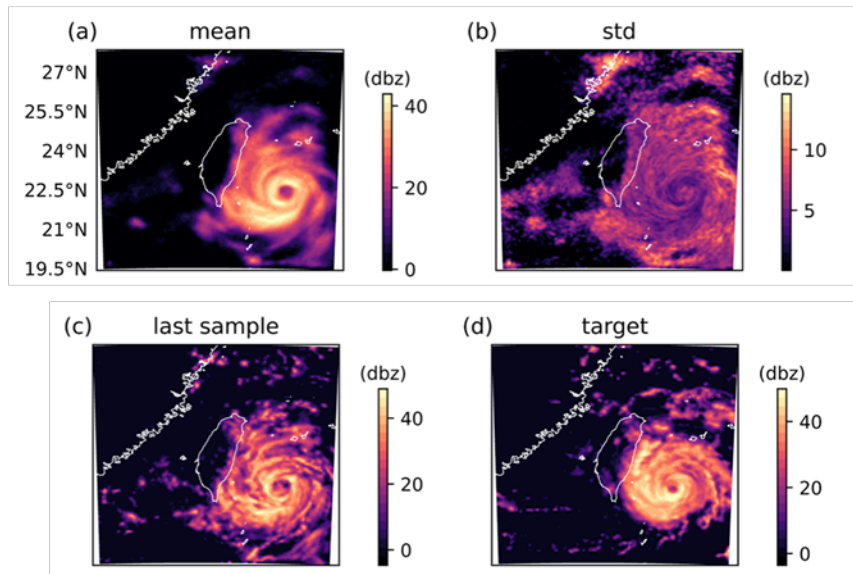


COASTAL DOWNSCALING

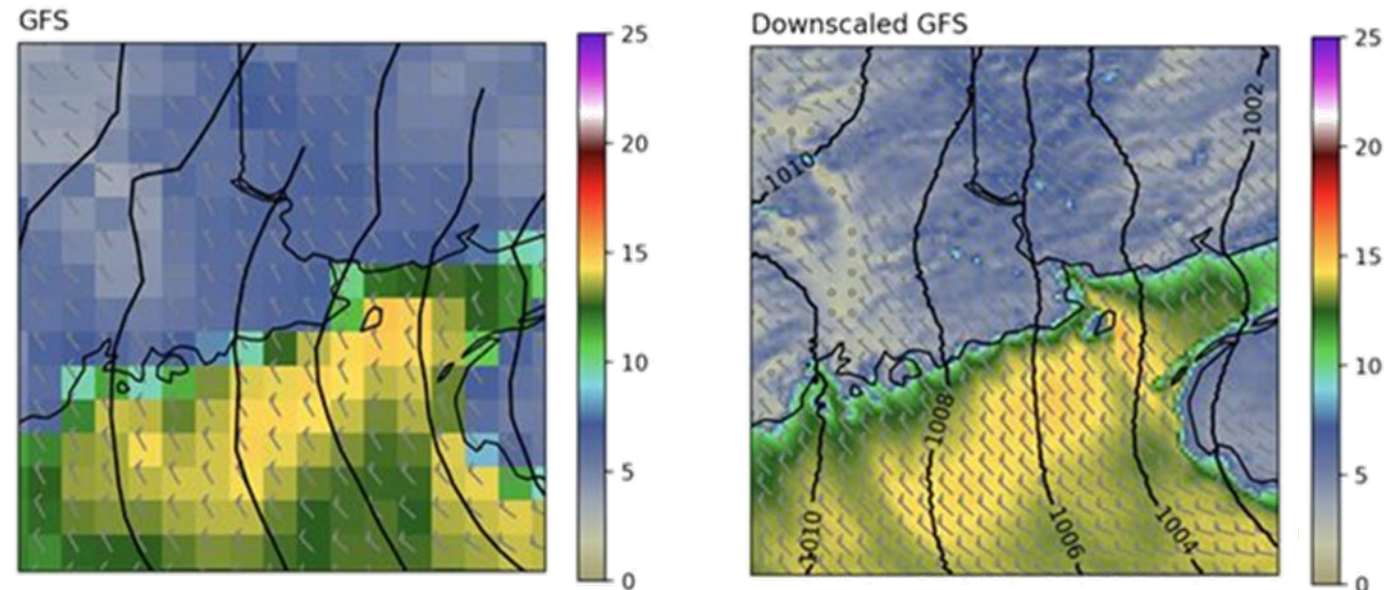


A *fidelity* limitation of this framework: *You must choose which parameters to downscale, and their resolution.* And taking advantage of investments from some of the wealthiest tech companies in the world: (i.e., NVIDIA)

CorrDiff Super-Resolution Downscaler



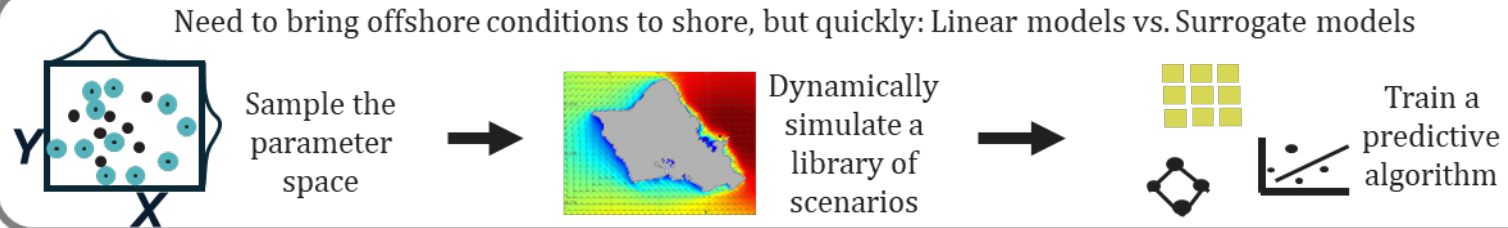
High resolution wind fields along the coast of Maine



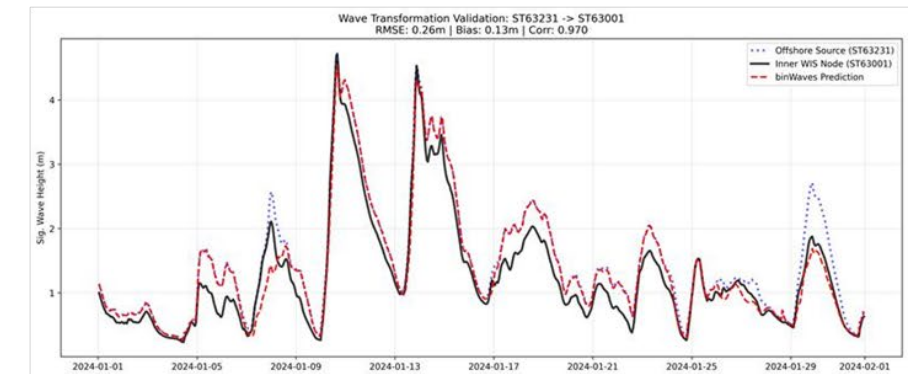
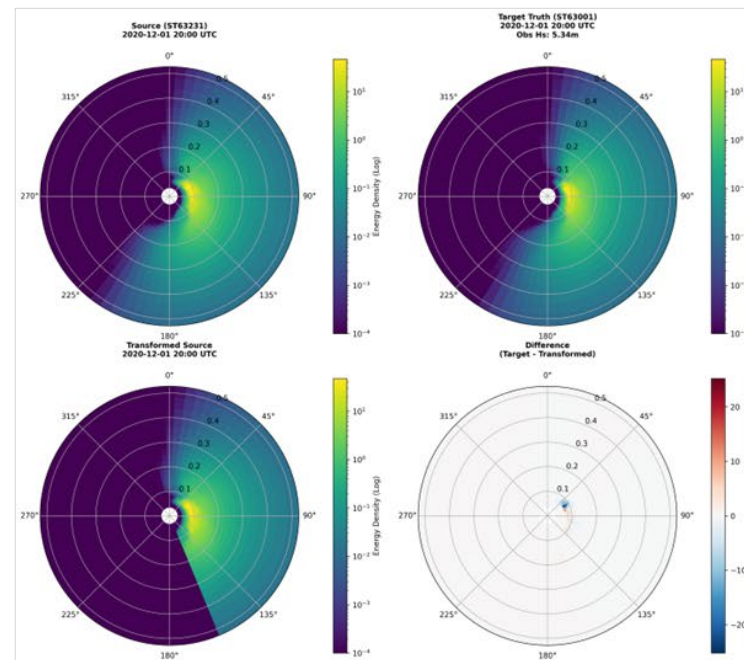
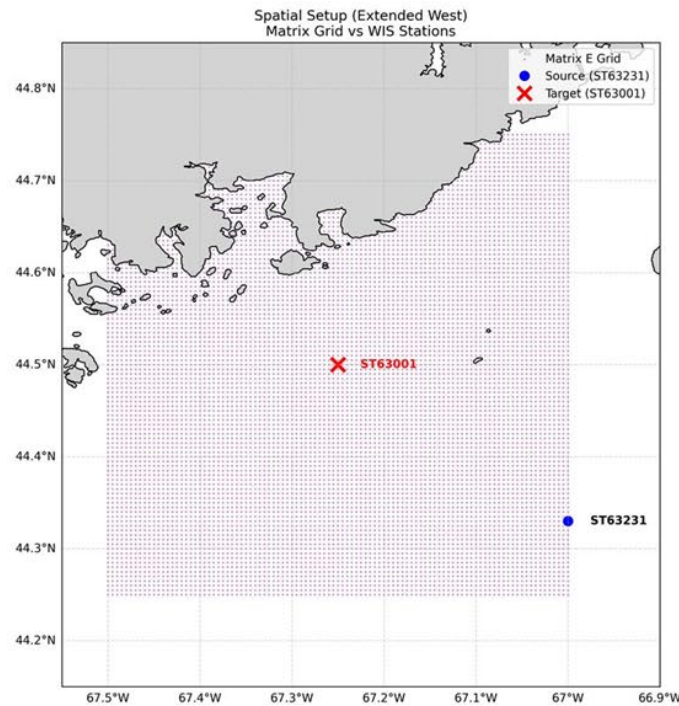


NEW METHODS

Coastal Downscaling



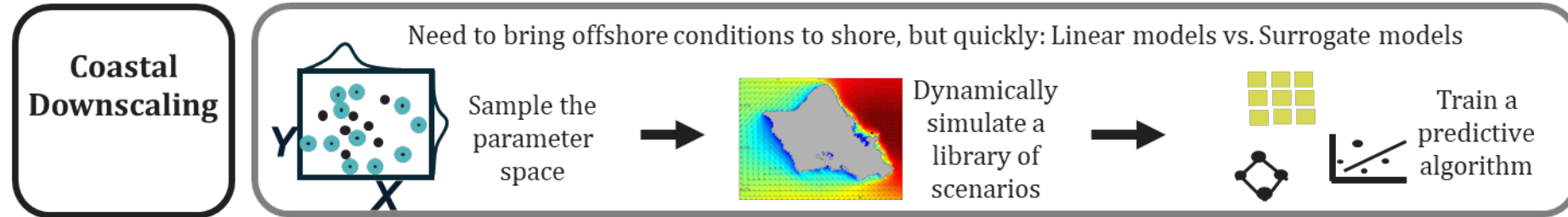
A *fidelity* limitation of this framework: *You must choose which parameters to downscale, and their resolution.*
And adopting new methods to provide multi-dimensional input parameters (i.e., Cagigal et al. 2024)



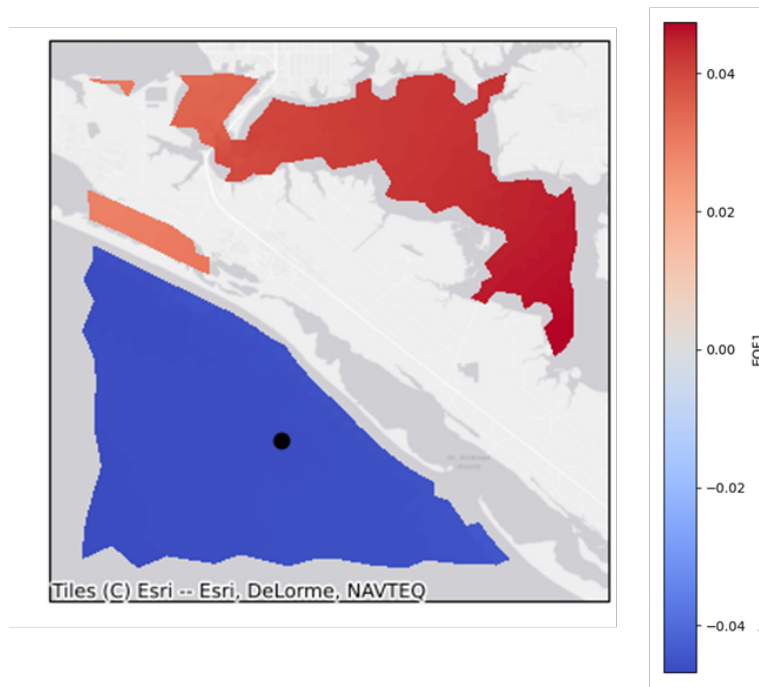
Credit to Tripp Collins



NEW DATASETS



A *fidelity* limitation of this framework: *You must choose which parameters to downscale, and their resolution.*
And taking advantage of new dataset that provide spatial resolution at the local scale.

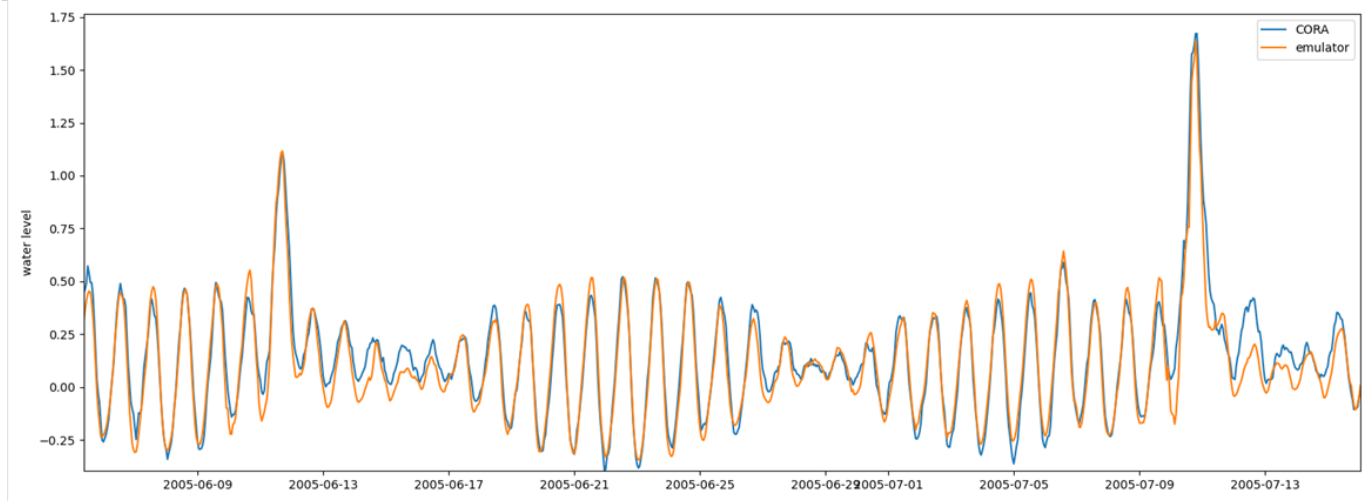


NOAA-CO-OPS/CORA-Coastal-Ocean-...

Notebooks to demonstrate working with NOAA's Coastal Ocean Reanalysis



[GitHub - NOAA-CO-OPS/CORA-Coastal-Ocean-Reanalysis-CORA: Notebooks to demonstrate working with NOAA's Coastal Ocean Reanalysis · GitHub](#)





WORKING ON VERSION 2.0

The entire framework is currently limited in its ability to inform compound flooding scenarios:

Need to include precipitation as a forcing parameter, but also an “impact” model that can simulate hydrodynamics of rainfall, runoff, ponding, groundwater, flow through inlets:

Options:

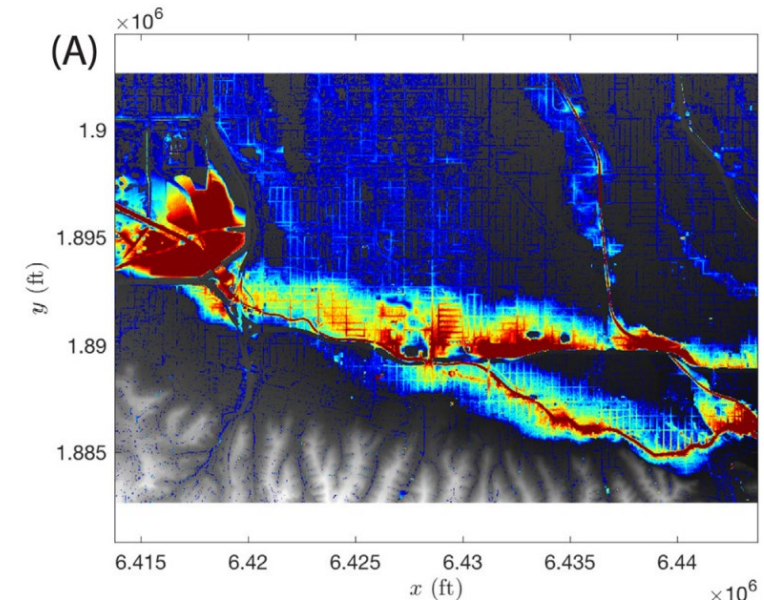
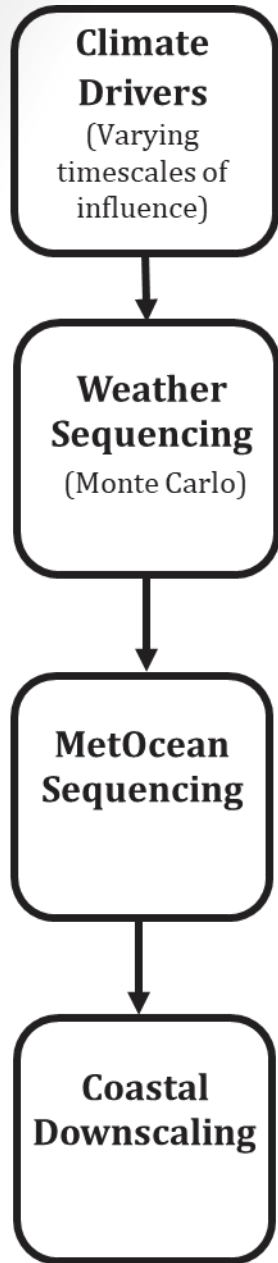
- Super-Fast INundation of CoastS:

<https://www.sciencedirect.com/science/article/pii/S0378383920304828?via%3Dihub>

- PRIMo: Parallel raster inundation model:

[PRIMo: Parallel raster inundation model - ScienceDirect](#)

GPU-enabled, can relatively quickly simulate a library of storms with time evolution, and can account for sub-terrain storm drainage systems





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